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Introduction

We conclude that housing cannot be understood with a narrowly financial approach that ignores space any more than it can be understood with a narrowly spatial approach that ignores asset markets.

– Glaeser and Gyourko, 2010

Most people participate directly in the housing market, either by renting or owning. Households spend a considerable share of their income on housing—whether it be paying rent, mortgages, or renovating their homes. But, houses serve not only as a place to live but also as a major store of wealth. For many, buying a house is the largest investment they will make in their lifetime. At the start of the 21st century, about two-thirds of Europeans and Americans owned their homes, with residential property constituting the largest part of their wealth (Badarinza, Campbell, and Ramadorai, 2016). In other words, for most households, their house is simultaneously a consumption good and an investment.

Historically, housing markets have been the focus of urban economics, which models houses as goods that produce services that can be consumed by living in them. In urban economics, the value of a house depends solely on the value of its housing services, which are typically a function of local amenities and economic conditions (Glaeser and Gyourko, 2010). The main aim of this literature is to explain spatial differences in economic activity and housing markets, with little attention devoted to the fact that housing is also an investment. Despite the central role of housing markets in today's economies and people's lives, surprisingly little macroeconomic and financial research had been conducted on them before the turn of the century. However, in 2007, the world's attention turned to the housing market as a wave of real estate foreclosures in the U.S. initiated a worldwide financial crisis with severe economic and political consequences. The tremendous boom (2000-2006) and bust (2006-2010) in housing prices and the subsequent financial crisis prompted substantial research on the sources of fluctuations in housing prices and how these interacted with the real economy (Davis and Van Nieuwerburgh, 2015; Piazzesi and Schneider, 2016). At the core of the new macro-financial models was a focus on houses as assets, whose changes in value strongly affected business cycle fluctuations, the transmission of monetary policy, and wealth distribution (e.g. Mian and Sufi, 2011; Kaplan, Moll, and Violante, 2018; Cloyne, Ferreira, and Surico, 2020; Kuhn, Schularick, and Steins, 2020). While these models are very successful at explaining national developments, they typically overlook the role of spatial heterogeneity in housing markets.

In my research, I have tried to integrate spatial heterogeneity into new asset pricing theories of housing, emphasizing that the value of a house as an investment also depends on its location. In particular, I apply asset pricing tools and theory to the study of housing prices in a spatial framework, thereby identifying and quantifying sources of risk and returns and how they interact with location in housing markets.

In the first chapter of my thesis, I focus on documenting stylized facts about the spatial distribution of returns to housing. In the second and third chapters of my thesis, I explore the drivers of housing returns by focusing on the roles of idiosyncratic housing price risk and liquidity. Finally, I examine how systematic regional differences in housing risk explain the growing regional gap in housing prices.

In *Superstar Returns? Spatial Heterogeneity in Returns to Housing*, which is coauthored with Moritz Schularick, Martin Dohmen, and Sebastian Kohl, we document the spatial distribution of total returns to housing and provide supporting evidence for its drivers. To conduct this analysis, we have assembled a new long run city-level dataset covering annual house prices and rents in twenty-seven prominent (”superstar”) cities across fifteen OECD countries over the past 150 years. For each superstar city within a country, we calculate long-term total returns on residential real estate investments as the sum of price appreciation and rent returns, and subsequently compare them to returns in other regions of the country. In constructing this dataset, we leveraged existing historical research, but, in most cases, we manually collected new house price and rental series from sources such as city yearbooks, newspapers, tax records, and notary archives.

Our data reveals that, over the long run, superstar cities have experienced lower total returns on housing in comparison to other regions within the same country. While house prices have grown more rapidly in these larger cities, the rental returns are significantly higher in more remote locations, resulting in overall higher returns in other parts of the country. An investment in the superstar cities within a country is associated with a yearly negative return premium of approximately 90-100 basis points relative to the national average returns.

The question arises: why are housing returns lower in large cities than in other parts of the country? We show that our key finding can be explained within a standard asset pricing framework, where excess returns outside large cities serve as compensation for higher risk. We then test this mechanism empirically and find that housing investments are indeed riskier outside large cities. First, we find that the covariance between housing returns and local income growth is considerably higher in more remote locations. This finding aligns with the fact that smaller cities are more exposed to industry-specific shocks, making the local housing markets less resilient to disruptions in the local labor market. Second, we find that housing markets in smaller cities are considerably less liquid and display higher idiosyncratic housing price risk. We define idiosyncratic risk as property-specific resale risk and show that homeowners in smaller cities face significantly more uncertainty about the sales value of their houses. Given that most homeowners do not diversify their housing portfolios, we should expect idiosyncratic housing risk to matter in equilibrium.

In the second chapter of my thesis, I use detailed transaction-level data to quantify the extent to which idiosyncratic risk impacts housing prices and returns. In *Price Uncertainty and Returns to Housing*, I present empirical evidence that residential properties with higher idiosyncratic price risk are, on average, sold at lower prices and yield higher total returns. I show that this result can be rationalized within a bargaining model, in which a risk-averse and non-diversified buyer faces future sales price uncertainty. Finally, I present empirical evidence that houses with higher idiosyncratic risk undergo a more uncertain trading process, thereby exposing their buyers to greater liquidity risk.

Housing prices result from a bargaining process between sellers and buyers, who often assign very different values to the same house. Consequently, the outcome of these negotiations is highly uncertain. This uncertainty is reflected in the fact that, depending on the houses' characteristics and location, it is harder to predict the sales price for some houses relative to others. In this paper, I examine the extent to which property-specific price uncertainty, or idiosyncratic risk, matters for housing prices and returns.

The primary analysis in this paper is based on a dataset that I constructed with co-authors (Amaral et al., 2023). This dataset comprises transaction-level information on the universe of residential real estate sales in the largest cities in Germany over the past 50 years. We built the dataset using machine learning Optical Character Recognition (OCR) techniques to extract information on real estate transactions from notary contracts.

Empirically, I measure price uncertainty as the predicted variance of the pricing errors from a hedonic housing price model. Leveraging the granularity of the German housing dataset, I measure property-level total returns, and show that houses with higher idiosyncratic risk are traded at lower prices and yield higher total returns. These results can be rationalised in a setting in which risk-averse and non-diversified buyers are only willing to pay a lower amount for a property whose future value is more uncertain.

What is driving price uncertainty? I find that properties with higher price uncertainty are more atypical, i.e. have fewer similar propeties on the market. Furthermore, properties with higher price uncertainty have a larger spread between the listing price and final transaction price, indicating a larger gap between the private valuations of the buyer and seller. Overall, the evidence shows that idiosyncratic price risk is driven by uncertainty about the liquidity of the house.

In the third chapter of my thesis I explore in more depth the relation between liquidity, location and housing prices. In *Urban Spatial Distribution of Housing Liquidity*, which is co-authored with Mark Toth and Jonas Zdrzalek, we examine how location, liquidity and prices interact in housing markets. By combining real estate online listings data with transaction data, we introduce a novel dataset that provides transaction-level measures of liquidity in large German cities over the past decade.

Empirically, we find that both housing liquidity and prices decrease with distance to the city center. Apartments located closer to the city center sell considerably faster and at prices much closer to their original listing value compared to apartments situated further away from the city center. Using search behavior data from online real estate platforms, we also find that the housing market becomes thinner with increasing distance from the city center. We refer to these new empirical findings as the urban liquidity gradient, which complements the well-established urban price gradient showing that housing prices decrease with distance from the city center.

To explain our empirical findings, we build a spatial search model of a housing market within a monocentric city. We show qualitatively and quantitatively that increasing travel costs to the city center can explain the joint urban spatial distribution of prices and liquidity. Using our calibrated model, we structurally estimate a spatial liquidity premium gradient, finding that buyers are willing to pay a 9% premium solely for the higher liquidity of apartments in the city center compared to the outskirts. This paper provides the first estimates of the spatial housing liquidity premium.

In the fourth and final chapter of my thesis, I analyse the consequences of heterogeneity in housing risk across regions. In *Interest Rates and the Spatial Polarisation of Housing Markets*, which is co-authored with Moritz Schularick, Martin Dohmen, and Sebastian Kohl, we reexamine the causes of regional housing price inequality. Using a novel long-term dataset of housing prices and rents for 27 major urban centers, we show that regional differences in housing prices have increased considerably more than differences in rents. This trend started in the 1980s, coinciding with the onset of declining interest rates. This poses a challenge to previous explanations for the increase in regional housing price disparities, which primarily relied on increasing regional differences in rental prices.

We build a spatial housing valuation model to demonstrate how a fall in real interest rates at the national level disproportionately affects the valuation of housing in regions with lower housing risk. The discount rate of the marginal buyer in large cities is relatively more affected by the fall in national interest rates, thereby increasing prices more in these cities. We argue that housing discount rates are location-specific, based on our finding that housing risk and returns are systematically lower in large cities, as explained in more detail in Chapter 1 of the thesis. Overall, this mechanism explains how prices can diverge across cities without corresponding rent divergence. We validate this mechanism by calibrating the model and showing it can precisely predict the long-term increase in regional price dispersion over the last 40 years.

This paper is the first to explore the consequences of regional heterogeneity in housing returns and risk, providing a new answer to a question that has already been extensively studied: 'Why do housing prices grow more in certain areas than in others?'

In summary, this dissertation provides a characterization of housing as an asset within a spatial framework, offering new insights into the risk-return relationship in real estate markets. Understanding this relationship is crucial for designing incentive-compatible and financially sustainable policies that can enhance the resilience and affordability of housing markets.

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Chapter 1

Superstar Returns? Spatial Heterogeneity in Returns to Housing*

Joint with Martin Dohmen, Sebastian Kohl, and Moritz Schularick

1.1 Introduction

Residential real estate is the most important asset in household portfolios, the main collateral of bank lending, and plays a central role in current macroeconomic models of aggregate fluctuations (Mian and Sufi, 2011; Berger et al., 2018; Kaplan, Moll, and Violante, 2018; Cloyne, Ferreira, and Surico, 2020). Moreover, housing is not easily diversifiable, meaning that households are typically very exposed to

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fluctuations in the value of their houses (Piazzesi and Schneider, 2016). In this paper, we show that significant return differences exist within residential real estate as an asset class, and that these differences are driven by the location of the asset. Using newly assembled long-run data for 15 economies, we demonstrate that there are systematic differences in risk profiles and asset returns between housing in large agglomerations and other parts of the same country.

The "housing market" is a collection of markets that differ along many attributes (Glaeser et al., 2014; Piazzesi, Schneider, and Stroebel, 2020). Households typically do not hold geographically diversified claims on housing portfolios, but rather individual properties in specific locations (Levy, 2021). The local nature of housing markets suggests that studying its geographical heterogeneity is key to better understand its effects on macroeconomic fluctuations (Piazzesi and Schneider, 2016). But so far we know very little about the spatial distribution of housing market risk and return.

Due to the absence of high quality data sets, research on housing markets has evolved slowly (Piazzesi, 2018). For this paper, we therefore built an extensive new city-level data set covering cities in 15 OECD countries and their hinterlands over the past 150 years. For the construction of the data set, we could partly draw on existing historical research. In most cases, however, we had to hand-collect house prices and rent series from yearbooks or primary sources such as newspapers, tax records, and notary archives. We complement this data set with two granular data sets covering returns for the cross-section of cities in the U.S. and in Germany. For the U.S., we combine the data set constructed by Gyourko, Mayer, and Sinai (2013) with data from the American Community Survey for the 2010-2018 period. For Germany, we hand-collected a data set on housing returns covering 127 small and large German cities.

These new sources allow us to establish a new and robust stylised fact: Over the long-run, there exists systematic variation in total returns on residential real estate between large cities and other parts of the same country. In particular, large agglomerations have witnessed lower total returns on housing than residential real estate markets in other parts of the same country. An investment in large cities comes with a negative return premium of about 100 basis points per annum. These return differences are a robust feature of the data across countries and time periods, and statistically highly significant. An annual negative return premium of around 1 percentage point accumulates to substantial return differences in the long run.

While housing prices in large cities grew faster in many cases than in the rest of the country (Gyourko, Mayer, and Sinai, 2013), rental returns were typically consistently lower such that taking rental returns into account reverses the spatial distribution of housing returns. The negative spatial correlation between capital gains and rental returns has recently also been documented by Demers and Eisfeldt (2021), but we can show, for the first time, that the differences in rental returns are larger and more persistent than the differences in capital gains, leading to higher long-run returns.[1] This key finding meshes with recent studies showing that more expensive neighborhoods within the same city saw lower total returns than cheaper neighborhoods over the last decade (Demers and Eisfeldt, 2021; Morawakage et al., 2022).

The second part of the paper shows that the spatial distribution of returns matches the spatial distribution of risk and liquidity in housing markets. In particular, we show that the co-variance of income growth with returns, idiosyncratic price risk and liquidity risk are positively correlated with returns across space. Our core finding regarding the lower returns in large agglomerations can thus be rationalized in a parsimonious rational expectations equilibrium of the housing market: higher returns outside the cities are a compensation for higher risk. Suppose that everything that makes large cities special – their diversified economies, large markets, amenities, and international linkages – also makes them safer places for investment. The present value of future housing services will be subject to less risk so that buyers are willing to pay a higher price and accept a lower return for housing investments. For remote locations to attract capital, they have to offer higher returns.

Our analysis in the second part supports this risk-based interpretation of the (negative) premium on large city real estate. On the one hand, the co-variance between housing returns and income growth is lower in large cities. Between 1950 and 2018, the co-variance between U.S. MSA-level income growth and MSA-level housing returns was significantly larger in smaller MSAs. On the other hand, households typically do not hold diversified housing portfolios and, therefore, are also exposed to idiosyncratic risk. We show that idiosyncratic housing risk is considerably higher outside the large cities. Using U.S. transaction-level data from Corelogic, we find that the idiosyncratic component of housing risk decreases with MSA size. As liquidity is low, home owners in thinner markets face a greater risk of not realizing the local market return at the point of sale. Real estate search engine data confirm a significant increase of housing market liquidity with city size. Recent work by Giacoletti (2021), Sagi (2021) and Kotova and Zhang (2019) also points to a close relationship between idiosyncratic risk and housing market liquidity.

We perform various robustness checks to back-up our key results. We use different rental yield benchmarks, study sub-periods and the effects of rent regulations, and vary the definitions of large cities. *First*, as our core finding is driven by differences in rental returns, we rebuild our main data set using independent, country-specific, present day rental yield benchmarks. The overall results remain very similar. Due to data constraints, our historical series do not explicitly take into account the segmentation between owner-occupied and the rental housing. However, our results hold both in cities with high and low homeownership rates, where the issue of market segmentation should be less pronounced or even non-existent. Moreover, recent research has used high-quality granular data to show that there is

1. As emphasized by Demers and Eisfeldt (2021), this result overturns the common wisdom that real estate in the coastal areas of the U.S. is a better investment than in fly-over cities.

little variation of price-to-rent ratios across market segments (Begley, Loewenstein, and Willen, 2021; Demers and Eisfeldt, 2021) in regions with high homeownership rates.

Second, although we are interested in long-run returns, we want to make sure that they are not driven by specific time periods. We separate the early historical parts of the sample, and also split the sample period in 1990. The same patterns can be found in the historical period as well as during the last three decades. *Third*, we divide our data set into different rent regulation and tax regimes. It turns out that our results are not driven by periods with strict rent controls or with different taxation of capital gains or rents. *Lastly*, we explore different definitions of cities, and experimented with different size cut-offs in different eras. Once more, none of this alters the new stylized facts that this paper uncovers: lower long-run returns in large agglomerations.

Previous literature: Our work contributes to a number of distinct research fields. The paper builds on and extends research on asset returns in housing markets (Lustig and Van Nieuwerburgh, 2005; Piazzesi, Schneider, and Tuzel, 2007; Piazzesi, 2018). It adds a new disaggregated perspective to the research on returns on national housing portfolios (Jordà et al., 2019) and brings an international comparative perspective to individual papers on housing returns in individual regions (Mian, Sufi, and Trebbi, 2015; Eichholtz et al., 2021; Keely and Lyons, 2022).

Our paper also speaks to the urban economics literature by bringing together house price data with rental yields, housing returns and measures of local housing market risk. While the existing literature has focused on the spatial distribution of economic activity (Glaeser, 2010) and implications for house prices (Saiz, 2010; Gyourko, Mayer, and Sinai, 2013; Hilber and Vermeulen, 2016), we point to another consequence of agglomeration: Other than having higher productivity and wage levels (Ahlfeldt and Pietrostefani, 2019), less concentrated labor markets (Desmet and Rossi-Hansberg, 2013), higher elasticities of urban costs (Combes, Duranton, and Gobillon, 2019) and more diversified industry compositions (Duranton and Puga, 2000), large cities also feature less housing risk.

This paper is also part of a nascent literature on the risk-return relation in housing markets (Case, Cotter, and Gabriel, 2011; Han, 2013; Peng and Thibodeau, 2017; Demers and Eisfeldt, 2021; Giacoletti, 2021; Sagi, 2021), and complements recent work by Hilber and Mense (2021) as it points to persistent differences in price-rent ratios between cities.

We also contribute to the literature on the role of housing for portfolio choice (Flavin and Yamashita, 2002; Cocco, 2005; Chetty, Sándor, and Szeidl, 2017; Martínez-Toledano, 2020; Gomes, Haliassos, and Ramadorai, 2021) by quantifying how households' exposure to housing risk changes with the location of their residential property. Finally, we speak to the rapidly growing literature on the drivers of return heterogeneity across the wealth distribution (Gabaix et al., 2016; Benhabib and Bisin, 2018; Bach, Calvet, and Sodini, 2020; Kuhn, Schularick, and Steins, 2020), by showing that that expensive and high-income locations provide lower total returns on housing.

The paper is organized as follows. The following section describes our new long-run data set and provides an overview of the series we have constructed (see also the detailed documentation in the Data Appendix). In the third section, we describe the novel stylized facts emerging from our data set and compare city-level and national-level housing returns. We establish our key finding that total returns are lower in large cities. Section four introduces two granular data sets for the U.S. and Germany and studies housing returns over the entire city-size distribution in both countries. In section five, we turn to the differences in housing risk as an explanation for the return differences. We show that housing risk is lower in large cities, both in terms of co-variance risk between excess returns and local income as well as due to smaller idiosyncratic shocks in more liquid markets. The last section concludes.

1.2 Spatial heterogeneity in housing returns: a new long run data set

This section introduces our new historical city-level data set. The data cover 27 cities over the long run: London, New York, Paris, Berlin, Tokyo, Hamburg, Naples, Barcelona, Madrid, Amsterdam, Milan, Melbourne, Sydney, Copenhagen, Rome, Cologne, Frankfurt, Turin, Stockholm, Oslo, Toronto, Zurich, Gothenburg, Basel, Bern, Helsinki, and Vancouver. The city-level data set contains house prices and rents as well as rental yields for every city. In the following, we briefly discuss the criteria we employed for the choice of cities and the methods used to construct the series. Details on the sources for each city, as well as a comprehensive list of all the new data series in this paper, can be found in the Data Appendix.

1.2.1 City sample

We focused our data collection on the largest cities within 15 developed countries. For each country, we define the largest cities in terms of 1900 population and include cities with a population share of more than 1% in 1900. To the extent possible, we also aimed to cover at least 10% of the 1900 country population in order to analyze a relevant share of the countries' housing markets. Selecting cities based on the population in 1900, instead of using current population, circumvents the problem of survivorship bias. A detailed discussion of city choice by country is provided in the Data Appendix. Urban systems evolve over time and so do the boundaries of cities. Over time, all cities and local housing markets grow either through incorporation of more and more suburbs or through the creation of metropolitan regions. We follow the administrative definitions in our sources which makes our city definition consistent *within* countries. City definitions are mostly identical for the rental and ownership markets.

Table 1.1. City choice and data coverage

City	Pop1900	Share pop	Country	House prices	Rents
London	6480	0.157	0.157	1895–2018	1870–2018
New York	4242	0.056	0.056	1920–2018	1914–2018
Paris	3330	0.082	0.082	1870–2018	1870–2018
Berlin	2707	0.048	0.078	1870–2018	1870–2018
Tokyo	1497	0.034	0.034	1950–2018	1950–2018
Hamburg	895	0.016	0.078	1870–2018	1870–2018
Naples	563	0.017	0.054	1950–2018	1950–2018
Barcelona	552	0.030	0.059	1950–2018	1947–2018
Madrid	539	0.029	0.059	1950–2018	1947–2018
Amsterdam	510	0.099	0.099	1870–2018	1870–2018
Milan	491	0.015	0.054	1950–2018	1950–2018
Melbourne	485	0.130	0.257	1880–2018	1901–2018
Sydney	478	0.128	0.257	1880–2018	1901–2018
Copenhagen	462	0.180	0.180	1938–2018	1885–2018
Rome	438	0.013	0.054	1950–2018	1950–2018
Cologne*	437	0.008	0.078	1902–2018	1890–2018
Frankfurt*	350	0.006	0.078	1897–2018	1895–2018
Turin	330	0.010	0.054	1950–2018	1950–2018
Stockholm	300	0.059	0.084	1875–2018	1894–2018
Oslo	227	0.102	0.102	1870–2018	1892–2018
Toronto	205	0.038	0.050	1900–2018	1921–2018
Zurich	150	0.045	0.098	1905–2018	1890–2018
Gothenburg	130	0.025	0.084	1875–2018	1914–2018
Basel	109	0.033	0.098	1912–2018	1889–2018
Helsinki	97	0.037	0.037	1946–2018	1946–2018
Vancouver*	69	0.013	0.050	1950–2018	1950–2018
Bern	64	0.019	0.098	1912–2018	1890–2018

Note: Cities are ordered by population level in 1900. Column 2 shows city-level population in 1900 in 1000 inhabitants. Column 3 describes the share of each city's population of total country population in 1900. Column 4 states the cumulative share from all cities in a respective country in our data set. Columns 5 and 6 describe data coverage from earliest to latest year of price and rent indices. For some cities there are gaps in the data coverage because of missing data, e.g. during periods of war and hyperinflation. City-level population data is taken from Reba, Reitsma, and Seto (2016) and country-level population from Jordà, Schularick, and Taylor (2017). For Cologne and Frankfurt, city-level population was below 1% of country population in 1900. However, the German Empire in 1900 had a considerably different area compared to Germany today. In 1950, the population in both Frankfurt and Cologne was above 1% of Germany's total population. The estimate for Vancouver is taken as the sum of Burrard and Vancouver city from the Canadian population census from 1901. Burrard became officially part of Vancouver in 1904.

The sample is summarized in Table 1.1. Data coverage of price and rent data is shown in columns 5 and 6. The sample starts in 1870, but some gaps remain. We have 7 decades of data for all cities and a balanced panel for the post-1950 period. Column 3 shows the cities' shares of the country populations in 1900 and column 4 the aggregated share of the country populations in 1900 which are covered by our sample cities.

1.2.2 Sources and methodology

This section briefly describes the sources of the data and the construction of the total return series. For all cities in our sample, we construct annual house price indices, rent indices and calculate total housing return series.

1.2.2.1 House price and rent indices

Whenever possible and of sufficient quality, we use house price and rent indices from existing research. An example is the return series for Amsterdam described in Eichholtz et al. (2021). In most cases, however, house price and rent indices are not readily available or the quality is insufficient. To construct the series, we first used data from a broad range of secondary sources such as city yearbooks, but in many cases we had to hand-collect new data from diverse primary sources. These consisted of newspapers, tax records, notaries, archives of real estate agents, and diverse other archival data. About half of the series are newly constructed.

The criteria to select appropriate sources mainly depended on data representativeness and availability. Whenever we had multiple choices, we used the source which provided the best coverage and the most details. The case of London provides an illustration where we could partly rely on data from previous research but had to close a large gap after World War II. The existing house price series cover the years before 1946 and after 1969. To connect the series, we hand-collected asking prices from real estate advertisement sections in newspapers. We focused on sales ads that provided enough information to build quality-adjusted indices.

Whenever micro-data was available, we relied on repeat-sales or hedonic regression methods. For instance, for Frankfurt we built a hedonic house price index from 1960-2018 using transaction level data from public sources and their archives. Whenever micro-level data was not available, we used data disaggregated by housing types and location inside a city to construct stratification indices.

Regarding the construction of rent indices, we primarily rely on rent indices from statistical agencies. Examples are rent indices that were constructed by city statistical offices for (city-level) CPI data. These mainly use repeated rents methodology. In other cases, when we were able to collect micro-level data, we relied on hedonic methods. For example, for the city of Oslo, we constructed a hedonic rent index for the period between 1950 and 1970 from newspaper rental advertisements. In other cases, we constructed stratification indices whenever possible, mainly relying on statistical publications. For example, in the case of Stockholm we used average rent by size of dwelling to construct a chained stratification rent index. We benchmark our rent indices with rents surveyed in housing censuses. Historically, such censuses were taken roughly every ten years and typically covered all rental units, providing a precise picture of the universal level of rents in a specific city.

All price and rent indices are deflated using country-level CPI data from Jordà, Schularick, and Taylor (2017), with a general national CPI including housing costs.

This is to compute real log returns at the city and country level, following the convention in the literature (Giacoletti (2021)). We also report the non-deflated results which not only leaves within-country differences intact, but even amplifies them because the deflator's largest and increasing component is housing costs. The technical definition of this component, particularly the owner-occupied cost and weighting, has been the subject of numerous within-country debates (Gordon and van-Goethem (2007)). Over the long run, there is no harmonized CPI excluding housing costs at the national level, let alone at the local level, which we could use. One alternative would be to take city-level CPIs which, however, are available only for a subsample of our cities. The differences between these city-level CPIs and between the city-level and national-level CPIs are negligible, with almost perfect co-movement and correlation (see Appendix 1.B). Deflating by the total national CPI is thus a reasonable but conservative choice, and the only available full-sample option.

For details on source and index construction by city, please refer to the Data Appendix. The resulting series cover a representative city-level housing portfolio that approximates the behavior of the value-weighted housing market within a city.[2]

1.2.2.2 Housing return series

We use house price and rent indices to construct housing returns series. As is well known, a house delivers two types of returns. First, the price of a house can change and this generates a capital gain (or loss). Secondly, a house delivers a consumption stream in the form of housing services. These can be sold to receive a cash flow by renting out the house. Alternatively, they can be consumed; in this case the owner receives the replication value as a cash-flow. Total returns on housing can be computed as:

$$\text{Total return}_t \;=\; \underbrace{\frac{P_t - P_{t-1}}{P_{t-1}}}_{\textbf{Capital gain}} + \underbrace{\frac{R_t(1-c)}{P_{t-1}}}_{\textbf{Net rent return}}\,, \tag{1.1}$$

where P_t is the house price at time t, R_t is the gross rent payment at time t and c are the total net operating costs as a share of R_t, which we describe in more detail below. Following this equation, the construction of city-wide (real) capital gains is straightforward using our house price indices. To construct rental return series, we estimated rent-price ratios, which we adjusted for nominal house price growth in the following manner: $Rent\ return = \frac{R_t}{P_t} * \frac{HPI_t^{nom}}{HPI_{t-1}^{nom}}$.

Rent-price ratio estimates are constructed following the rent-price approach used in Jordà et al. (2019) and Brounen et al. (2013). To do so, we first use benchmark rent-price ratios for the end of our sample period in 2018. We again follow

2. In Appendix 1.A we compare hedonic house price indices for different market segments for Cologne. We show that over a period of 30 years, trends for all residential market segments were similar.

Jordà et al. (2019) and use benchmarks calculated from realized net operating income yields of real estate investors. These were provided by *MSCI*, which collects data from a variety of real estate investors for large cities around the world. Yields are defined net of total operating costs, which are composed of maintenance and property taxes as well as other costs. Other costs included are management costs as well as the cost of vacancies, letting and rent review fees, ground rents and bad debt write-offs. Finally, we use our rent and price indices to calculate rent-price ratios over time:

$$\frac{RI_{t+1}}{HPI_{t+1}} = \left(\frac{RI_{t+1}/RI_t}{HPI_{t+1}/HPI_t}\right)\frac{RI_t}{HPI_t}. \tag{1.2}$$

The disadvantage of this methodology is that possible measurement errors accumulate over time due to extrapolation. To account for this, we collected historical rental yield benchmarks to verify our rental yield series. For a detailed summary of the sources we use please refer to Table 1.2 and the Data Appendix. We predominantly relied on secondary sources or newspapers. For all sources, we aimed at collecting rental yield estimates out of rent and price data for the same buildings. All benchmark rent-price ratios are constructed net of depreciation and running costs. If direct estimates for these costs were not available, we instead relied on estimates for depreciation and running costs in percentage of gross rent inside the country in question from Jordà et al. (2019). Whenever the rent-price approach estimates diverge from these historical sources, we adjust the estimates to the historical measures as detailed in the Data Appendix. Another potential bias in our return series could arise from the ratio of net to gross income. Evidence in section III.C of Jordà et al. (2019) and in Figure 3 of Demers and Eisfeldt (2021) shows that the ratio of net to gross income stayed relatively constant over time and that there are very small differences across regions over the last 30 years. Additionally, we also do not find systematic differences in the ratio of net to gross income across 22 different U.S. cities both for 2007 and 2020 using MSCI data. The Figure can be found in the Data Appendix.[3]

1.3 Returns in large cities

In this section, we first establish the main stylized facts on long run housing returns in large cities. We then proceed to analyze trends in capital gains and rental

3. Throughout the paper we follow the existing literature and measure housing returns in log points instead of percentage points. The main reason is that log returns are time compoundable, whereas percentage returns are not. Moreover, log returns have preferable distributional features and are approximately equal to percentage returns for small numbers. For a full rationalization please refer to the Data Appendix.

Table 1.2. Overview of the rental yield benchmark sources

City	Main Source	Alternative Source	Homeownership rate (in %)
London	MSCI	–	49.5
New York	MSCI	–	30.8
Paris	MSCI	Numbeo	33.1
Berlin	MSCI	Numbeo; GA; IVD	14.8
Tokyo	MSCI	Numbeo	45.8
Hamburg	MSCI	Numbeo; GA; IVD	23.3
Naples	MSCI	Numbeo	55.5
Barcelona	MSCI	Numbeo	64.0
Madrid	MSCI	Numbeo	73.2
Amsterdam	MSCI	Numbeo	27.2
Milan	MSCI	Numbeo	68.0
Melbourne	Corelogic	Numbeo	72.8
Sydney	Corelogic	Numbeo	65.2
Copenhagen	MSCI	Numbeo	50.6
Rome	MSCI	Numbeo	70.6
Cologne	MSCI	Numbeo; GA; IVD	26.0
Frankfurt	MSCI	Numbeo; GA; IVD	19.2
Turin	MSCI	Numbeo	65.7
Stockholm	MSCI	Numbeo; Catella	62.2
Oslo	Numbeo	Catella	75.5
Toronto	MSCI	Numbeo	54.6
Zurich	MSCI	–	9.0
Gothenburg	MSCI	Numbeo; Catella	55.7
Basel	MSCI	–	13.7
Helsinki	Numbeo	KTI	48.0
Vancouver	MSCI	Numbeo	48.5
Bern	MSCI	–	16.6

Note: This table lists all the the main and alternative sources we used to construct reliable rental yield benchmarks. Additionally, we also provide information on the homeownership rate in the respective city for the year 2011. More details about the sources and methods used to construct these series and on all the other series from various authors we used can be found in the Data Appendix.

returns, as well as their contributions to total returns, and compare large cities to the rest of the country.

We start with summary statistics on log real housing returns and its components for our new data set. The left-hand panel of Figure 1.1 shows average log housing returns for the full time period and the right-hand panel for the period post-1950.[4] City-level total housing returns have been in the four to six log point range per

4. A table with summary statistics by city in log points, including standard deviations, can be found in the Data Appendix. Additionally, we also included a table with average percentage point (simple) returns for comparison to other literature.

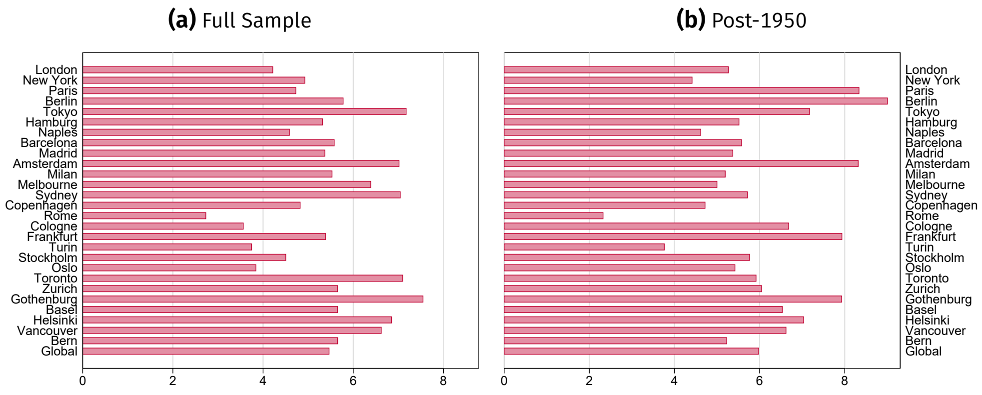

Figure 1.1. City-level real average total housing returns (log points)

Note: The figure shows average total real housing returns in log points for all cities in our main sample. The series have been deflated using the national CPI series from Jordà, Schularick, and Taylor (2017). Panel (a) covers the entire sample for return data in our main data set, which is the subset of years for which rent and house price data (minus 1 year) exist, compare Table 1.1. Panel (b) shows average housing return data by city starting in 1950.

year, with some differences across the cities in our sample. Toronto, Amsterdam, Gothenburg, Tokyo and Sydney are the cities with the highest long run returns. The panel on the right shows that housing returns were higher in the post-1950 period and reached about 6 log points.

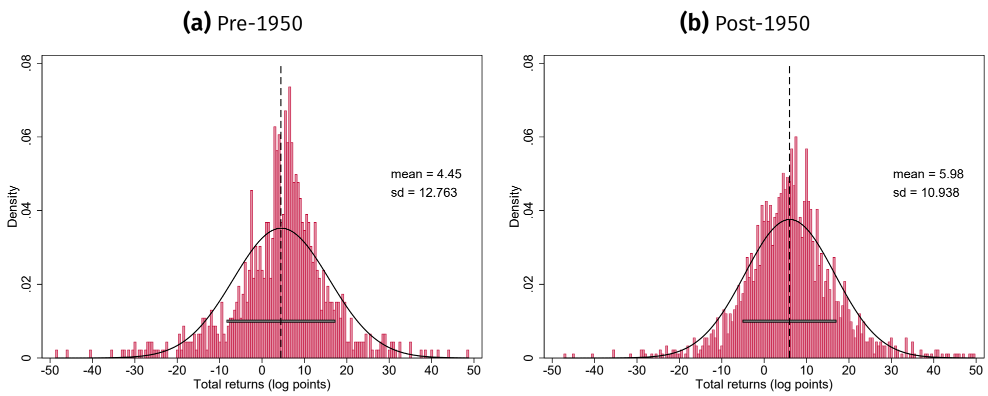

Figure 1.2. Distribution of annual real housing returns (log points)

Note: The figure shows the distribution of annual total housing returns in log points for all cities in our main sample. The series have been deflated using the national CPI series from Jordà, Schularick, and Taylor (2017). Panel (a) covers the entire sample of cities until 1950; compare 1.1. Panel (b) covers the entire sample of cities after 1950.

Figure 1.2 plots the distribution of annual log real housing returns for the pre- and post-1950 period. While housing returns were on average lower in the pre-1950 period, they also displayed a higher standard deviation than in the post-1950 period, which is apparent in a thicker left-tail in the pre-1950 period. This does not come as a surprise, considering that this period featured two World Wars, the Great Depression and large variations in housing policies. Post-1950 large city returns were close to 2 percentage points higher with a lower standard deviation.

Rental returns represent approximately 67% of total housing returns over the last 150 years. Panel (a) of Figure 1.3 shows that, although the relative share of rental returns has been quite volatile over time, it has remained by and large the main contributor to total housing returns. In fact, for all cities in our sample, with the exception of Milan, rental returns represent more than 50% of total housing returns in the long run. This result is in line with the findings in Jordà et al. (2019) and Demers and Eisfeldt (2021).

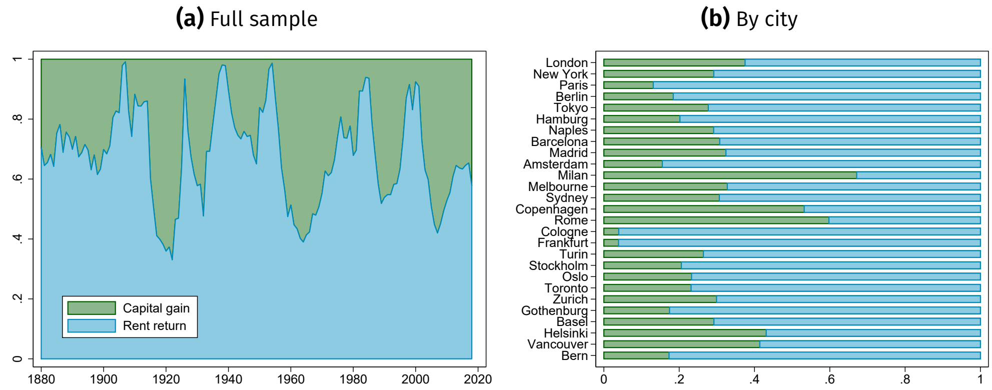

Figure 1.3. Share of total log returns, 1870-2018

Note: Panel (a): The displayed series are 10-year lagged moving averages, e.g. the share of capital gains for the year 2010 is the average share of capital gains between 2000 and 2010. All cities get an equal weight. This panel shows the share of log capital gains and log rental returns in the sum of both. In the few cases when moving average log capital gains have been negative, we take the absolute value of the moving average log capital gains instead. Panel (b): Average share of log real capital gains and log rental returns by city for the whole period for which we have data for the city.

1.3.1 Large agglomerations vs. national housing markets

In the next step, we merge our city-level data set with national housing returns from Jordà et al. (2019) in order to compare returns in the large cities to those in the rest of the country. Jordà et al. (2019) compiled data on capital gains, rental returns and total housing returns for nationally diversified housing portfolios that represent the weighted sum of housing markets within a specific country. We extend their data to 2018 using country-level house price and rent indices from national statistical agencies and substitute house price series for Japan after 2008 and for Sweden after 1952, because series with better methodology and coverage became available. For details see the Data Appendix.

The national housing portfolios include the large cities in our sample. For transparency and comparability reasons, we will still compare the larg•e city returns to the national series from that study. But we also calculate returns of a "rest of the country" portfolio as the weighted average of the housing returns in the other locations in the country. National returns can be expressed as:

$$\textit{National return}_t \;=\; w_{t-1} * \textit{Large city return}_t \;+\; (1 - w_{t-1}) * \textit{RoC return}_t, \quad (1.3)$$

where w is the relative weight of the large city in the respective national housing series.[5] Using equation 1.3 and our large cities return series, we can approximate the housing returns in the rest of the country (*RoC return*) by subtracting the large cities in our data set from the national series. As data on market capitalization are lacking, we use population shares as portfolio weights to construct return series for the rest of the country (excluding the large cities). All city-level and national population data for this calculation are taken from United Nations (2018). Due to higher housing prices in large cities, using population weighting will give a smaller weight to the large cities than a market capitalization weighted index. As such, the rest of the country returns that we back-out from national series likely mark a lower bound.

In some cases, the geographical coverage of the national housing series is too narrow in the pre-World War II era to allow a meaningful comparison between the large cities and the rest of the country. In the Data Appendix we included a table which details the geographical coverage of the national house price series by country. For the comparison between large city returns and the rest of the country, we will therefore focus on the 70-year period between 1950-2018 for which the national housing series have a wide enough geographical coverage. Nonetheless, the overall results are very similar when we study returns over the entire sample period (see Appendix 1.C.3).

To guide the reader through the results, we start with Paris as an example. Our data show that an investor who bought an apartment in Paris in 1950 realized an average yearly capital gain of 4.85 log points over the period until 2018. The annual rental return in Paris was 3.66 log points on average, resulting in a healthy

5. As a way of confirming our rest-of-the-country calculation, we use the MSA-level data set by Gyourko, Mayer, and Sinai (2013) to calculate the average combined total housing return for all American MSAs except New York. Given the differences in the source of the data and the methodologies, we obtain a very close result to our rest-of-the-country estimate, with the difference in average yearly log total return between 1950 and 2018 ranging between 0.4 and 0.6 percentage points depending on the weighting scheme for the rest of the country.

total annual return of 8.33 log points. This means, for instance, that investments in Parisian residential real estate beat investments in the French equity market by a substantial margin, even on an unleveraged basis.

How does this investment return compare to the rest of France? An investment in the French national housing portfolio over the same 70-year period saw annual capital appreciation of 4.48 log points, somewhat lower than Paris. As Paris is a substantial part of the French national portfolio, the difference must be driven by other regions in France, in which house prices have risen about half a percentage point less per year than in Paris. However, the picture changes when we bring in rental returns, which were substantially higher in the rest of the country (5.06 vs. 3.66) and more than offset Paris' advantage with respect to capital gains. Total housing returns were 9.15 per annum for the rest of France and thus about 85 basis points per year higher than in Paris. Despite higher capital appreciation, Paris underperformed the rest of France with respect to total returns on housing investment.

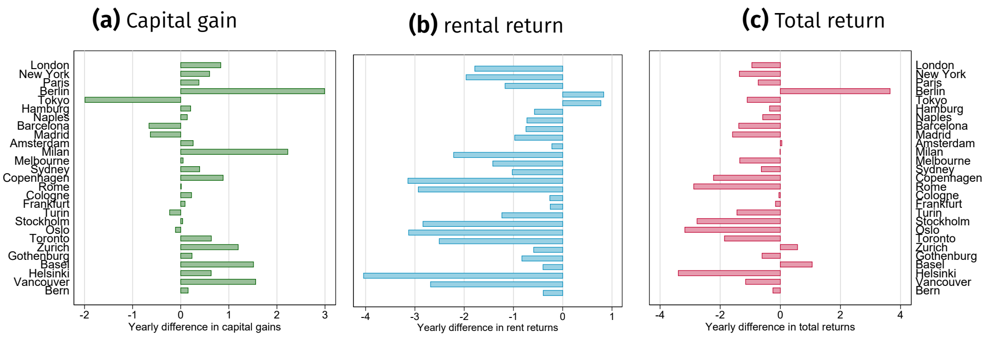

Figure 1.4. Average differences in city-level and national returns (log points), 1950-2018

Note: This graph shows the mean difference in log capital gains (Panel (a)), log rental returns (Panel (b)) and log total returns (Panel (c)) between the city-level and the respective national portfolio by city. The period covered is 1950 to 2018, except for German cities, Tokyo and Toronto, because the national data only starts in 1963, 1960 and 1957 respectively.

In Figure 1.4, we broaden the perspective to all 27 large cities in the sample and compare them to their national real estate markets. Figure 1.4 shows differences in capital gains (left), rental returns (middle) and total housing returns (right) between 1950 and 2018 for each city relative to the national returns.[6] A general pattern can be easily discerned. Just like in the French case, capital gains are higher in nearly all large cities. The only major exception is Tokyo – a city that experienced a severe real estate crisis in the early 1990s. Real house prices in Tokyo were still only one third of their 1990 level in 2018, while house prices in other parts of the

6. Appendix Table 1.C.1 presents the numbers including standard errors of paired t-tests.

country stand at 65% of the 1990 level. Rental returns are generally much lower in the big agglomerations, and overall returns are lower.[7]

Table 1.3. City-level and national yearly housing returns (log points), 1950-2018

	27 large cities				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.25	1.82	0.43* (0.23)	1.64	0.61** (0.26)
Rent return	3.55	4.94	-1.39*** (0.04)	5.21	-1.65*** (0.05)
Total return	5.72	6.68	-0.95*** (0.23)	6.76	-1.04*** (0.26)
N	1767				
	Only largest city/country				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.45	2.12	0.33 (0.30)	1.99	0.46 (0.34)
Rent return	3.53	5.17	-1.63*** (0.06)	5.41	-1.88*** (0.07)
Total return	5.89	7.18	-1.29*** (0.30)	7.30	-1.41*** (0.34)
N	1061				

Note: The table shows averages of city-level and national log capital gains, log rental returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. Rest of country (RoC) returns are calculated as national housing portfolio returns share after taking out the returns of the 27 national large cities. We use previous year population shares as weights of the portfolio share of our cities, such that the estimate should be interpreted as a lower bound. The upper panel shows the results averaged over all 27 cities in our main data set. The lower panel shows the results only for the cities, which had the largest population in their respective countries in 1950 in our data. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 1.3 formalizes the analysis of different large city/national housing portfolio definitions, together with paired t-tests for the equality of means between city and national housing portfolios: the table shows capital gains, rental returns and

7. The main exception is (West) Berlin. As data for East Berlin is missing between 1945 and 1990, the Berlin portfolio covers only West Berlin after World War II. The higher housing return in West Berlin might, however, not be surprising when considering the unique history of the city. Prior to the fall of the Berlin Wall and the reunification of Germany in 1990, Berlin was not only heavily supply constrained, but also potentially a very risky place to invest in taking the political tensions between the Soviet Union and the West into account. Additionally, the reunification of Germany itself could be regarded as a very large positive shock to (West) Berlin, potentially keeping housing returns off of their equilibrium path for several years. The other outliers are much smaller and typically featured exceptionally high capital gains compared to the respective national index. These, in turn, might be driven by large positive shocks to the city development. The main example is Basel, which had a rapidly growing economy since World War II and now is the region with the highest GDP per capita in Switzerland. Within Switzerland, the Canton Basel-Stadt (Nuts-2 region) had by far the largest GDP per capita in 2018, which was nearly twice as high as that of the Canton of Zurich (source: Federal Statistical Office Switzerland, Table je-e-04.02.06.03, published 21.01.2021).

total returns at the large city-level (Column 1) and for the national housing portfolios as defined in Jordà et al. (2019) (Column 2). Column (4) shows the population-weighted return for the rest of country (excluding the large cities), as defined above. The lower panel narrows the large city definition to the single largest city in each country (New York, London, Paris, etc.), providing an even stronger large city vs. rest of country comparison.[8]

At 2.25 log points, capital gains were about 43 basis points higher in the 27 large cities than in the national portfolio, and 61 basis points higher than in the rest of the country. Rental returns, in contrast, were lower in the large cities, with a difference of 1.39 or 1.65 log points, depending on the comparison portfolio. The higher rental returns outside the large cities more than compensate for the lower rate of capital appreciation. Our overall benchmark estimate is that in the long run, total returns in the large cities were 95-100 basis points lower per year than in the national portfolio and rest of the country.

The lower panel of Table 1.3 focuses only on the largest city within each country (measured by 1950 population). For this sample, the average difference between the city-level and the rest of the country grows to 1.41 log points per year. The average total return of the national housing portfolio is around 7% per annum, meaning that large city returns are about 15% lower.

While Demers and Eisfeldt (2021) also show that cities with higher capital gains have lower rental returns, they do not show that the spatial difference in rental returns are larger than the ones in capital gains. Finally, our results are also in line with the existing evidence that more expensive neighborhoods saw lower total housing returns than cheaper neighborhoods in the last decade (Demers and Eisfeldt, 2021; Morawakage et al., 2022).

1.3.2 Further tests

Capital gains are higher in large cities, but they are more than offset by lower rental returns, resulting in lower overall returns. In the following, we will subject this core finding to a number of additional tests. First, we use alternative rental yield benchmarks. Secondly, we show that our results hold in the older historical period as well as in more recent decades. Finally, we study the potential role of rent regulations. Moreover, a discussion of the effect of taxation can be found in Appendix 1.D, where we show that differences in real estate taxation do not affect our results. Furthermore, we show that our main results also hold when using the nominal series, i.e., the return series not adjusted by the CPI. Please refer to Appendix 1.C.1 for the results.

8. We use the largest city per country within our data set. This implies that Toronto is included although Montreal was the largest city in 1950, because housing data for Montreal is missing.

Alternative rental yield benchmarks: The data used to calculate rental returns is assembled by professional real estate investors. They are based on rental yield benchmarks net of maintenance, management and other costs. As our core finding rests on the differences in rental returns between large cities and the rest of the economy, we recalculate returns with alternative rental yield benchmarks taken from country-specific sources or from the user driven online database Numbeo.com. For more detailed information on the sources please refer to Table 1.2. The alternative estimates potentially provide broader coverage of the housing market but might be less precise.

Table 1.4. City-level and national yearly housing returns (log points), 1950-2018

	Alternative Benchmarks					
	27 large cities			Only largest city/country		
	Cities	National	Difference	Cities	National	Difference
Capital gain	2.25	1.82	0.43* (0.23)	2.57	2.13	0.45 (0.29)
Rent return	3.32	4.94	-1.62*** (0.04)	3.42	5.20	-1.78*** (0.06)
Total return	5.50	6.68	-1.18*** (0.23)	5.90	7.22	-1.32*** (0.29)
N	1767			1004		
	Standard Benchmarks					
	Until 1990			Post 1990		
	Cities	National	Difference	Cities	National	Difference
Capital gain	2.67	2.21	0.46 (0.37)	1.69	1.31	0.38* (0.22)
Rent return	3.73	5.37	-1.63*** (0.07)	3.31	4.36	-1.06*** (0.04)
Total return	6.31	7.47	-1.16*** (0.37)	4.94	5.62	-0.68*** (0.22)
N	1011			756		

Note: The table shows averages of city-level and national log capital gains, log rental returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parentheses) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. The upper panel shows the results averaged using alternative rental yield benchmarks from country-specific sources. The left-hand side shows the results averaged over all cities in our main data set. The right-hand side shows the results for the cities which had the largest population in their respective countries in 1950. The lower panel shows the results using the standard benchmarks from MSCI for the years from 1950 to 1990 and from 1991 to 2018. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

The upper panel of Table 1.4 shows the results with alternative rental return data. If anything, the alternative data accentuate the differences in rental returns and suggests that the differences between market segments within cities do not play a major role. In the Data Appendix we show the summary statistics of our main data set and individual city returns with the alternative rental yield benchmarks. The differences are minor.

Subperiods: Driven by limited data availability, most of the recent literature on housing returns focused on developments in the last two or three decades. A natural question to ask is whether our results also hold for the most recent period, which saw a particularly pronounced increase in real estate prices (Knoll, Schularick, and Steger, 2017), as well as the emergence of global superstar cities.

For an initial test, we split our sample period in 1990. The lower panel of Table 1.4 shows the results for the 27 large cities relative to the national index. Our key results also hold for the most recent period: large city returns have also been significantly lower in the post-1990 era. The same is true for the largest city in each country. Additionally, Appendix Table 1.C.4 presents moving averages over the entire time period.

Rent regulations: Could stricter rent regulations in large cities account for the lower rental returns compared to the rest of the country? To start with, from an asset pricing perspective, rent regulations should not by themselves have an effect on housing returns since they only regulate the cash-flow received from the asset. As the price of an asset is determined by the discounted value of future expected cash-flows, we would expect house prices to adapt to different cash-flows, such that rent-price ratios would be unaffected. Rent controls could, however, influence expectations about future rents, which could affect house prices and current returns.

As an empirical test for the effects of rent controls on returns, we use the rent control index from the *Rental Market Index (ReMaIn) Database*. The database compiled by Kholodilin (2020) uses rent legislation since 1914 in 64 countries to create standardized indices measuring the existence and intensity of rent control, tenant protection and housing rationing. The results in Table 1.C.5 in Appendix 1.C.5 confirm that, independently of rent control regimes, capital gains are higher and rental returns lower in the large cities compared to the national average. The absolute difference between large cities and the national returns is even slightly higher in stricter rent control regimes.

Extreme returns:. In Figure 1.2, we present the distribution of annual log total returns for our 27 city sample. It is apparent from the Figure that there is a non-negligible number of outliers. In particular, during the post-1950 period, the period for which our main results hold, we have 19 cases of annual total returns that exceed 40%. These outliers are due exclusively to capital gains, i.e., periods in which there are considerable jumps in our housing price series for specific cities.

To ensure that our results are not being driven by these outliers, we excluded these outliers and conducted the main analysis again. As shown in Table 1.C.6 in Appendix 1.C.6, all our main results hold when excluding the outliers. As an additional robustness test, we collected specific information on each one of these 19 outliers to confirm that they are not noise. In section 5.2 of the Data Appendix, we include both qualitative and quantitative evidence that supports our findings. For example, the housing price series for Sydney and Melbourne grew by more than

50% in 1950, which can be explained by the fact that the strict housing price controls which had been introduced in Australia in 1942 were lifted at the end of 1949 (Stapledon, 2007).

In order to account for the impact of negative outliers, we reproduced the main analysis while excluding all city-level total housing returns that fell within both the top 5% and bottom 5% of the distribution. The detailed results are provided in Table 1.C.7 of the Appendix section 1.C.6. Notably, the key findings of the paper remain highly robust and maintain their statistical significance.

1.4 Housing returns over the city-size distribution

In this section, we study housing returns across the entire cross-section of cities within two countries: the U.S. and Germany. The choice of these countries allows us to analyze two national real estate markets that belong to two different "housing regimes" (Kohl, 2017). U.S. cities are dominated by owner-occupied, single-family dwellings with light rent regulation but comparatively strong homeownership subsidies. The German housing market is characterized by tenant-occupied, multi-story buildings and a soft rent-control regime without much home ownership support (Kholodilin and Kohl, 2021). In typologies of housing regimes (Schwartz and Seabrooke, 2008), these two countries often end up on opposite sides and are seen as representative of different approaches in housing policy (Kemeny, 1995).

We use two different data sets that cover the complete size distribution of cities. The approach and the methodology are the same within data sets. The central question is whether the findings from the long-run comparison of large cities with other parts of the country apply more broadly across the entire city-size distribution.

1.4.1 U.S. superstars redux

For the U.S., we rely on the data set compiled by Gyourko, Mayer, and Sinai (2013), to which we add two additional observations for 2010 and 2018 from the *American Community Survey* (ACS).[9] Their original data cover the near-universe of MSAs from 1950 to 2000 at decadal frequency from the *Census on Housing and Population*. Gyourko, Mayer, and Sinai (2013) find large differences in house price appreciation across metropolitan areas over a period of 50 years.

9. To make the data comparable, we build MSA level aggregates using the official borders from 1990, as done by Gyourko, Mayer, and Sinai (2013). All our results stay virtually the same when we restrict our analysis to the original data set covering only the years until 2000 and, if anything, become stronger if we restrict the sample to only MSAs with full county coverage in 2010 and 2018. Results are available on request. All the data is on the MSA-level, but to simplify we still refer to them as "cities" here. For details about data construction please refer to the Data Appendix and Gyourko, Mayer, and Sinai (2013).

Due to the decadal frequency of the data, we calculate total housing returns as averages of capital gains and rental yields over 10-year periods. Moreover, we use rental yields instead of rental returns, because the decadal data does not allow us to precisely calculate rental returns. Rental yields are the inverse of the price-rent ratios calculated by Gyourko, Mayer, and Sinai (2013), then adjusted downwards for maintenance costs and depreciation. We assume that one third of gross rents are spent on these costs across all locations.[10]

We define the largest cities as being the largest five percent of sampled MSAs in terms of 1950 population. Choosing the largest 5% as the cutoff allows us to focus on exceptionally large and economically important cities. The size of these cities will be far from the mass point of cities, as the city size distribution is approximately a Pareto distribution.[11] In the following, we compare these top-5% of cities to all other MSAs in the data set and, secondly, to the smallest 5% of MSAs. But our overall results do not depend on these cutoffs.

Table 1.5. Difference in housing returns (log points) for 316 US MSAs, 1950-2018

Sample	Capital gain	Rental yield	Total return	N
Large vs rest	0.13 (0.21)	-0.67*** (0.16)	-0.52*** (0.15)	2184
Large vs small	-0.20 (0.25)	-0.63*** (0.20)	-0.80*** (0.20)	217
GMS superst. vs rest	0.53*** (0.13)	-0.68*** (0.11)	-0.17* (0.10)	1936
GMS superst. vs small	0.44** (0.19)	-0.55*** (0.18)	-0.13 (0.18)	347

Note: The table shows differences in housing returns between large cities and the rest of the sample or small cities. It covers 316 MSAs at decadal frequency between 1950 and 2010 and additionally the year 2018. Differences are measured as coefficients in a random effects panel regression of the dependent variable (log capital gain, log rental yield and log total housing return respectively) on a large city dummy and year fixed effects. Standard errors (in parentheses) are clustered at the MSA-level. Large cities are defined as being at or above the 95th percentile of the MSA population distribution in 1950 from census data. The second row shows the same, but comparing large cities only to small cities, which are defined as being at or below the 5th percentile of the MSA population distribution in 1950. The third row compares the superstar cities defined in Gyourko, Mayer, and Sinai (2013) to the other MSAs. In this comparison, we reduced the sample to the 279 MSAs included in the original analysis of the aforementioned authors. Note that we use rental yields instead of rental returns, because using decadal data, rental returns cannot accurately be calculated. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$

Table 1.5 presents by now familiar patterns. Rental yields are considerably lower in large cities compared to all other cities or to small cities. The absolute difference in total returns is estimated as between 50 and 80 basis points per year and hence somewhat smaller than in the international sample. This can be expected as we include more large cities.

10. While the rental yields
11. See e.g. Eeckhout (2004) or Duranton (2007).

The third row shows the comparison of the “superstar” cities as defined in Gyourko, Mayer, and Sinai (2013) with the rest of the city distribution,[12] but extended to 2018. Using this city sample, the difference in capital gains is significantly positive. This is not surprising, because the authors sample their superstar cities based on exceptionally high house price growth. For these cities too, the difference in rental yields is significantly negative and larger in absolute values than the difference in capital gains.

Thanks to the detailed data, we can also sort all cities into size deciles ordered from smallest to largest MSA. We split the first and last decile again to get a more precise picture of the tails of the distribution. Average total log returns within each

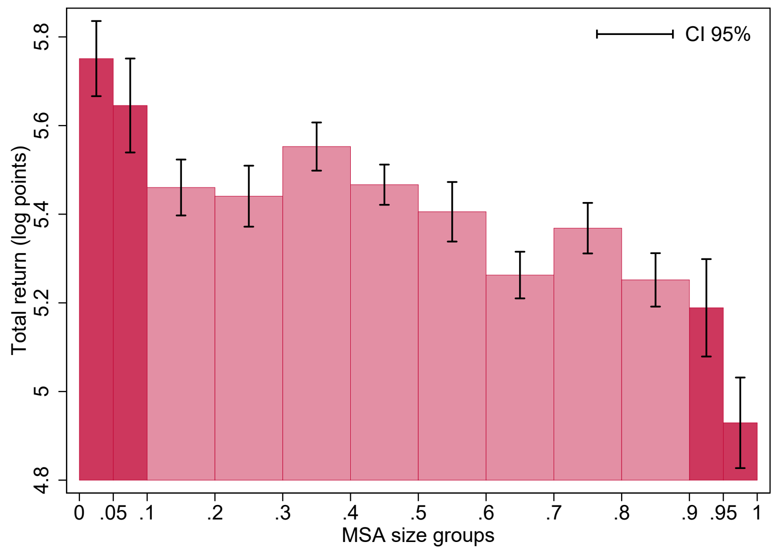

Figure 1.5. Total returns for 316 MSAs (log points) by population size, 1950-2018

Note: All returns are log returns. Cities are divided into bins based on the size of MSA population in 1950. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half. As the data for American MSAs only exist at decadal intervals, we are not able to construct rental returns. Rental yields are, however, used as a decent approximation of rental returns.

bin are plotted in Figure 1.5, which shows that overall housing returns decrease with city size. The relation is not perfectly monotonic across all size bins, but clearly visible overall.[13] The results in Table 1.5 are based on a comparison between the largest 5% of MSAs, encompassing 15 MSAs, and the rest of the country. To ensure that our results are not influenced by low statistical power, we ran the regression in the first row of Table 1.5 10,000 times, in each run randomly selecting 15 MSAs

12. We use the *ever_superstar* variable of the original data set, extended to the years 1960, 2010 and 2018. The authors exclude MSAs that do not meet the population threshold of 50,000 in 1950.

13. Results for equity markets are similar. The "big vs small" factor is also not linear across all the size bins and is much stronger for the tails of the distribution; compare Fama and French (1993).

from the original sample. In Appendix 1.E, we present the distribution of coefficients for total returns, rental returns, and capital gains, along with their respective p-values. For both total returns and rental returns, the results demonstrate that the coefficients for the largest 15 MSAs significantly deviate from the distribution of the random MSAs, and the p-values are uniformly distributed between 0 and 1. This confirms the statistical robustness of our findings. Regarding capital gains, the results are different. The coefficient for the largest 15 MSAs falls within the distribution of coefficients for the randomly selected MSAs, indicating that higher capital gains may not be a statistically robust result.

Cross-sectional differences in vacancy rates. If lower-quality properties in smaller cities do not get rented out, it could potentially introduce an upward bias in our rental yield estimates. This is because the rental yield calculations would be limited to higher-quality housing, leading to an incomplete representation of the rental market. The rental return differences we observe between small and large cities might then be explained by the fact that, on the other hand, in larger cities, houses from across the complete quality distribution are rented out.

To test this hypothesis, we gathered data on rental vacancy rates at the census tract level for all 384 metropolitan statistical areas (MSAs) in the U.S. from the American Community Survey for the years 2010 and 2020.[14] To approximate the quality of the housing stock, we classified the census tracts in each MSA based on their housing value. With this data in hand, we analysed the vacancy rates along the distribution of housing value for large and small MSAs.

Among the least expensive census tracts of the smallest MSAs in the U.S. the highest rental vacancy rate was 17.3%, while in some of the largest MSAs the least expensive census tracts had in some case more than 30% vacancy rates in 2010. This example suggests that vacancy rates do not significantly decrease with the quality of the housing stock. In fact, as we show in the appendix 1.G, vacancy rates even increase slightly with housing value for small MSAs. Only in the large MSAs does it seem to be the case that vacancy rates decrease with housing value. To ensure that our results are not being driven by census tracts, which are mostly composed of owner-occupied housing and, thus, have very volatile rental vacancy rates, we conducted a similar analysis using rental value as a measure of the housing stock quality and we found the same results.

1.4.2 German cities

For Germany, we constructed a novel data set for this study that covers 42 (West) German cities between 1974 and 2018 at annual frequency. The data set covers only comparably large cities that correspond to urban municipalities excluding rural

14. Census tracts are statistical subdivisions of counties that have on average 4,000 inhabitants.

hinterlands.[15] We extend the data to 127 (West) German cities from 1992 onward in a data set that covers the near-universe of (West) German cities. We exclude Eastern Germany, because data coverage mostly started later and Eastern German cities might be fundamentally different to West German ones at the beginning of our sample period. The data set is constructed using market reports of the German Real Estate Association and one of its predecessors.[16] These market reports surveyed local real estate agents and collected city-level observations for various market and quality segments. For the period from 1989 onward, the source allows us to directly use annual estimates for rental yields, such that we only have to rely on the rent-price approach discussed above for some years. We provide more information on the data sources and methods in the Data Appendix.

We start with the comparison of large cities and other cities (or the smallest 5% of cities). To do this, we sort cities by their 1975 population.[17] As for the U.S., we define large cities as being at or above the 5% largest of the size distribution. Table 1.6

Table 1.6. Difference in housing returns (log points) for 42 German cities, 1975-2018

Sample	Capital gain	Rent returns	Total return	N
Large vs rest	0.47 (0.57)	-0.91*** (0.34)	-0.45* (0.25)	1848
Large vs small	1.03 (0.72)	-1.58*** (0.43)	-0.57* (0.35)	264

Note: The table shows differences in annual housing returns between large cities and the rest of the sample or small cities. It covers 42 major German cities between 1975 and 2018. Differences are measured as coefficients in a random effects panel regression of the dependent variable (log capital gain, log rental return and log total housing return respectively) on a large city dummy and year fixed effects. Standard errors (in parenthesis) are clustered at the city-level. Large cities are defined as being at or above the 95th percentile of the city population distribution in 1975. The second row shows the same, but comparing large cities only to small cities, which are defined as being at or below the 5th percentile of the city population distribution in 1975. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$

confirms an identical pattern for Germany: lower total returns in the larger cities. The return gap grows when we compare large to small cities. We also study the more comprehensive housing return data starting in 1992. The results are shown in the Data Appendix.

Rental yield comparability. As with the American data set, the reason behind small cities outperforming larger ones is primarily attributed to the considerably smaller rental yields in the latter. In the previous section, we conducted several robustness checks to ensure that our rental yield measurements were not biased.

The German data set offers an excellent opportunity to compare rental yields across cities directly. This is possible because we have a time-series of rental yields

15. The average size of cities covered is approximately 418,000 inhabitants in 1975, with a standard deviation around 414,000 and a minimum of approximately 31,000.

16. The *Immobilienverband Deutschland (IVD)* and its predecessor *Ring deutscher Makler (RDM)*.

17. Source: Statistical office of Germany: *Gemeindeverzeichnis, Gebietsstand: 31.12.1975, Statistisches Bundesamt.*

for each city in the sample, eliminating the need to estimate rental yields using rental and price series, as done in the main analysis. Moreover, the rental yield series are derived using the same method for all cities in the sample, making them highly comparable.

In Figure 1.6, we present two binscatters illustrating the net rental yields based on the city population in 1989. These plots demonstrate a strong and significant negative relation between yields and population for both samples—one starting in 1973 and the other in 1989. The difference between panels (a) and (b) is due to the sample starting in 1973 containing a smaller number of cities, exclusively consisting of large cities, thereby leading to a stronger negative correlation in panel (b).

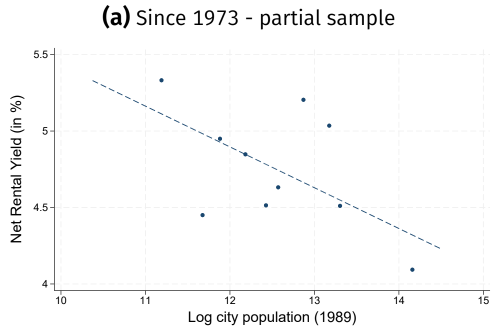

Figure 1.6. Net rental yield and population size

Note: The figure shows a bin scatter of city-level net rental yields from IVD by population in 1989 for 42 West German cities (panel (a)) and 127 West German cities (panel (b)). The net rental yields are residualized for year effects. Population data is taken from the "*Gemeindeverzeichnis*" of the German Statistical Office.

Using data for the cross-section of cities in both the U.S. and Germany, we have confirmed that the largest cities tend to have lower total housing returns than other housing markets in the same country. In the next section we discuss a framework that rationalizes these findings with differences in risk and present supportive empirical evidence.

1.5 Housing risk and return

Both in the long-run historical data and for the city-size distribution in the U.S. and Germany, we found that in big agglomerations: (i) capital gains tend to be higher, (ii) rental returns lower, and (iii) the difference in rental returns larger than the difference in capital gains so that total returns are lower in large cities. While there exists an extensive body of literature that documents the differences in capital gains and elucidates their driving forces, comparatively less attention has been directed to understanding the spatial distribution of total returns. In this section, we begin by reviewing the existing literature and show how it explains the spatial pattern of capital gains. Subsequently, we narrow our focus on housing risk as a potential factor that can explain the observed empirical distribution of total returns across regions.

There are different factors that potentially contribute to the observed higher capital gains in larger cities. National population growth and the trend of urbanization have significantly increased the demand for housing in cities over the past few decades. However, the housing supply, which is particularly inelastic in large cities (Saiz, 2010), has failed to keep pace with this surging demand, resulting in a substantial rise in house prices in the largest cities (Gyourko, Mayer, and Sinai, 2013).[18]

There has also been a large increase in the proportion of college graduates and higher-income households in the largest cities over the past two decades (Couture and Handbury, 2020), thereby exacerbating regional disparities in income. While the significant influx of college graduates was concentrated in the downtown areas of large cities (Couture and Handbury, 2023), housing prices increased more generally in larger cities as a result of the gentrification process affecting the surrounding neighborhoods (Guerrieri, Hartley, and Hurst, 2013). This process of income sorting (Diamond and Gaubert, 2022) has been demonstrated to significantly widen the gap in regional housing prices (Van Nieuwerburgh and Weill, 2010).

Overall, this body of literature is founded on the premise that price increases have been more significant in larger cities due to variations in fundamental factors, such as stringent housing supply constraints or increasing demand for housing due to higher incomes. However, these forces potentially also drive up rents, such that the net effect for rental returns is unclear. Thus, within this theoretical framework, the net impact on total returns remains uncertain – specifically, whether large cities over or underperformed the rest of the country. As a result, the key lies in comprehending how rental yields are distributed across different geographical areas and the extent to which they contribute to total returns.

Both in our international sample as well as in the U.S. and Germany samples, we find that rental yields are persistently smaller in the largest cities. This result aligns with the findings in Demers and Eisfeldt (2021), who show empirically that cities with higher prices exhibit lower net rental returns.[19] Additionally, our empirical analysis shows that the differences in rental yields outweigh the differences in capital gains.[20]

18. Empirical evidence presented by Hilber and Vermeulen (2016) demonstrates that a more inelastic housing supply leads to more pronounced house price growth in response to increasing demand. In Appendix 1.F, we present additional evidence that housing supply is particularly inelastic in large cities.

19. We show in Appendix 1.H that city size and the level of prices are very strongly positively correlated.

20. Although Demers and Eisfeldt (2021) confirm the result that larger cities underperform smaller cities by around one percentage point per year, the differences they find are not statistically

These results are consistent with the idea that returns in smaller cities should compensate investors for higher exposure to financial risk. In an asset market equilibrium with rational expectations and risk-averse housing investors, risk-adjusted returns should equalize across space, such that investors are indifferent between investing in different locations. As demonstrated in Appendix 1.I, a corollary of this principle is that areas with greater risk will correspondingly yield higher total returns and rental returns.

This framework also finds support in the empirical evidence that rental yields reflect expected total returns rather than expected rental growth (Campbell et al., 2009; Plazzi, Torous, and Valkanov, 2010; John H. Cochrane, 2011) in housing markets. From it follows that spatial differences in rental yields should reflect spatial differences in expected returns. These spatial differences in rental yields persist over time, as housing demand shocks impact both prices and rents in the long run, ultimately leaving rental yields mostly unchanged.[21]

To understand whether differences in risk can actually explain our main findings, we will quantify different measures of housing risk at the city-level in the subsequent sections of this paper.

1.5.1 Two sources of housing risk

Examining the difference in housing investment risk between cities, we will consider two separate potential sources of risk. On the one hand, housing market returns in small cities could be more correlated with consumption growth, providing less consumption insurance. On the other hand, real estate in more remote locations could exhibit higher idiosyncratic volatility, as it is typically traded in smaller and less liquid markets. Both types of risk are conceptually independent. We will first define the two concepts of risk and argue why they should be priced in housing markets. Then, we will discuss how we measure both types of risk and provide empirical evidence on the spatial distribution of risk in housing markets.

In standard asset pricing, risk premia arise as a result of the co-variance between asset returns and marginal utility, where the latter is typically approximated by consumption growth (John H Cochrane, 2009). In housing markets, it could be the case

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significant and, as such, differ from our results. This can be explained by the authors' use of a sample comprised predominantly of large cities, as well as their focus on an extraordinary and relatively short period of price expansion (1986-2014). The source that the authors use, the American Housing Survey, has historically focused primarily on relatively large cities. Furthermore, the analyzed sample period starting in 1986 does not include the 1970s, a decade characterized by relatively low price growth and higher rental yields (Jordà et al., 2019; Eichholtz et al., 2021). This omission limits the consideration of a period when rental yields had a more significant impact on total returns.

21. Indeed, the data reveals a decline in rental yields across both large and small cities from the 1980s to 2022, coinciding with a fall in interest rates. Amaral et al. (2021) analyze the relation between these two factors in more detail and explore the consequences for the spatial distribution of housing prices.

that the co-variance of local housing returns and consumption differs across large and small cities. On the one hand, it can be anticipated that larger cities possess more diversified economies, leading to reduced exposure to industry-specific shocks and a weakened covariance between housing returns and consumption growth. Additionally, the heightened exposure of these cities to foreign or non-local investors might moderate covariance, given that these investors typically demonstrate lower concern for local risks.[22] On the other hand, high income households have increasingly relocated to large cities with housing price appreciation (Couture and Handbury, 2020). This phenomenon establishes a positive correlation between income growth and house price appreciation in these regions. The relative strength of the aforementioned effects remains uncertain, and this is an aspect we aim to investigate by approximating consumption growth through local income growth and subsequently calculating the covariance between income growth and excess housing returns. Importantly, the co-variance with total housing returns is important when the marginal buyer is an investor. In fact, Sinai and N. S. Souleles (2005) show that when the marginal investor is a homeowner, a house serves as a hedge against rent volatility and, as such, the net risk of owning a house will decline with the co-variance in future housing costs.[23] Thus, larger cities can offer more secure housing markets due to the increased co-variance of housing costs both within individual large cities and across them.[24]

A second potential source of risk is idiosyncratic housing risk. In the case of housing, there are good reasons to think that idiosyncratic risk is priced. This is because houses are large, indivisible and illiquid assets and most home-buyers are owner-occupiers that own one house in a specific location and not a diversified housing portfolio (Piazzesi and Schneider, 2016). As a result, standard assumptions of models of diversified portfolios do not necessarily apply in housing markets and idiosyncratic risk will be priced as Merton (1987) showed. In fact, current estimates show that at least half of the price volatility of a house is idiosyncratic, meaning it is specific to the property (Piazzesi and Schneider, 2016; Giacoletti, 2021). Higher returns in small cities could be a compensation for higher exposure to idiosyncratic risk. To test whether this is in fact true, we calculate the idiosyncratic component of house price risk following the approach pioneered by Giacoletti (2021).[25]

22. Recent studies suggest that foreign investors contribute to heightened house prices in major international cities such as London, New York, or Paris, with their investment decisions primarily influenced by economic factors in their home regions (Badarinza and Ramadorai, 2018; Cvijanović and Spaenjers, 2021).

23. This thesis has been empirically confirmed in Paciorek and Sinai (2012) and Sinai and N. Souleles (2013).

24. Although this sounds like a realistic hypothesis, we are unaware of data that would allow us to test it.

25. Note that as idiosyncratic risk represents a source of transaction risk, it holds a central role when the marginal buyer is an investor or a homeowner.

1.5.2 Co-variance risk

The following holds for a utility-maximizing household that allocates resources between consumption and different investment opportunities:[26]

$$ln\mathbb{E}[R_{t+1}] - lnR_f \;=\; \gamma \;\; Cov\left[ln\left(\frac{C_{t+1}}{C_t}\right), lnR_{t+1} - lnR_f\right], \tag{1.4}$$

where R_{t+1} is the total return on the asset in the next period, R_f is the return on the risk-free asset, γ the risk-aversion parameter and $\frac{C_{t+1}}{C_t}$ is consumption growth. In other words, an asset that has a greater co-movement with consumption features a higher risk and, therefore, risk averse agents ($\gamma > 0$) request a higher excess return. Unfortunately, to the best of our knowledge long-run data on consumption at the regional level does not exist. Instead, we approximate consumption growth with regional income growth. An asset is riskier when it has a higher correlation with future income as it cannot be used to hedge against income shocks, and can even amplify them.

To calculate the co-variance between MSA-level income growth and MSA-level excess housing returns, we turn to U.S. Census data, described above in section 1.4.1. These data provide a measure of total housing returns and of family income growth over time. It is important to note that the data have decadal frequency. This implies that we compare the correlation of log excess housing returns and log income growth over long time periods.[27]

We first calculate MSA-specific co-variances as: $Cov_s = Cov(R_s - R_f, y_s)$, where R_s is total real log housing return for MSA s, R_f is the risk-free rate approximated by total real log returns on short-term U.S. T-bills and y_s is average real log income growth in MSA s. Hence, $R_s - R_f$ is the excess return on housing in MSA s. We calculate the co-variances for the period between 1950 and 2018.[28] We then test whether these co-variances are smaller in large MSAs. The results are depicted in Table 1.7 row 1. The co-variances of income and excess housing returns are significantly smaller in large MSAs compared to the rest. The difference in co-variances becomes larger when we compare the largest MSAs to only the smallest ones. Appendix 1.L shows results for the entire distribution of MSAs as well as estimated betas from a consumption based asset pricing model (CCAPM).

26. John H Cochrane, 2009.

27. By focusing on the 10-year averages, we are averaging out the cyclical evolution in consumption growth. This is in line with Parker and Julliard (2005), who show that the co-variance between current asset returns and cumulative consumption growth explains the cross-section of expected returns to a much greater extent than the co-variance between the asset's return and contemporaneous consumption growth.

28. Note that given the decadal frequency of the data, we have overall 7 data points for each variable MSA combination. For summary statistics on the returns and income growth please refer to Table 1.L.2 in the Appendix.

Table 1.7. Differences in co-variances for different MSA sortings, 1950-2018

Sorting	Large vs rest	Large vs small	Rest vs small
By MSA size	-0.55** (0.273)	-1.94*** (0.573)	-1.49*** (0.496)
By total returns	0.36 (0.416)	0.60 (0.448)	0.27 (0.167)
N	316	31	316

Note: The first row shows differences in the co-variance between income growth and log excess total returns by MSA size. For clarity the differences in co-variances are multiplied by 10,000. Large MSAs are defined as being at or above the 95th percentile of the MSA population distribution in 1950. Small MSAs are defined as being at or below the 5th percentile of the MSA population distribution in 1950. In column 3 we show the differences between small MSAs and the rest of the MSAs. The second row shows differences in total log housing returns between MSAs with large total housing returns and the rest of the sample or MSAs with smaller total housing returns. MSAs with large returns are defined as being at or above the 95th percentile of the MSA average total log housing returns distribution between 1950 and 2018. MSAs with small returns are defined as being at or below the 5th percentile of the MSA total log housing returns distribution between 1950 and 2018. In column 3 we show the differences between small MSAs and the rest. Differences are measured as coefficients in a cross-sectional regression of the dependent variable (co-variance) on a large MSA dummy (columns 1 and 2) or on a rest MSA dummy (column 3). Robust standard errors are in parentheses. Overall, we use estimates for 316 MSAs between 1950 and 2018. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

In the same spirit, the data allow us to test whether high return MSAs exhibit higher co-variances between housing returns and income, as the CCAPM predicts. In the lower half of Table 1.7 we sort MSAs by housing returns and compare co-variances for high and low return MSAs. We find evidence that return co-variances with income are lower in low return cities. This being said, the statistical significance is mixed. The results are borderline significant at the 10%-level ($p = 0.105$) only in the last column where we compare the lowest return MSAs (that tend to be the largest MSAs in terms of population) with all other MSAs. As can be seen in the middle column, the mean difference between co-variances in high vs. low return markets is particularly large, but it is not significant in the decadal data that we have at our disposal. Future research will have to rely on new types of data sets with more granular consumption series and higher frequency return data to pin down these differences more firmly. For now, we conclude that the available long-run data for the U.S. suggest that housing risks are higher in small cities as income co-varies more strongly with local housing returns. MSAs with low returns also tend to have smaller co-variances between returns and income growth than others.

1.5.3 Idiosyncratic house price risk

To test for differences in idiosyncratic risk, we use a combination of transaction-level price data from Corelogic and county-level house price indices from FHFA and Zillow.com for American MSAs over the past three decades. The focus will be on the U.S. because, to the best of our knowledge, equally detailed and micro-level house price transaction data do not exist for other countries.

Importantly, these estimates of idiosyncratic risk build on sales data and mark a lower bound for estimates of the idiosyncratic risk differences between large and small markets. In Appendix 1.N, we demonstrate that in large cities rental markets are substantially more liquid, rental vacancy rates are lower and less volatile, which reduces the uncertainty that a landlord faces over his future income stream. Moreover, Sagi (2021) has shown that for commercial real estate, including income streams does not significantly affect the volatility of property-level returns.

We estimate idiosyncratic house price risk as the unexplained variation in sales-level capital gains after controlling for: (i) market-level price changes (at the county level), and (ii) common house and transaction characteristics in the following equation:[29]

$$\Delta p_{i,l,t} = \Delta v_{l,t} + BX_i + \sigma_{l,idiosyncratic}\ \varepsilon_{i,t}, \tag{1.5}$$

where $\Delta v_{l,t}$ is the growth in local county house prices, BX_i is a vector of house and transaction characteristics, which includes zip-code and time fixed effects, and $\sigma_{l,idiosyncratic}\ \varepsilon_{i,t}$ is a sales-specific shock. We measure idiosyncratic risk as the standard deviation of sales specific shocks for properties within a specific MSA. Using data from *Corelogic* on repeat-sales of single family homes for the period between 1990 and 2020, we can estimate annual idiosyncratic risk in 248 MSAs, covering around 86% of the U.S. population in 1990. We describe the data sources and the methods used to estimate idiosyncratic house price risk in more detail in Appendix 1.K and in the Data Appendix.

1.5.3.1 Idiosyncratic risk across space

Figure 1.7 plots our measure of idiosyncratic house price risk across different MSA-size bins, showing that it decreases substantially with MSA size. Between 1990 and 2020, average idiosyncratic risk in the smallest MSAs was 12.34% of the house sales price, but about 25% lower in the largest MSAs at 9.28%. The measure of idiosyncratic house price risk is orthogonal to local housing market fluctuations and is therefore independent from the co-variance risk that we looked at above.[30] In Appendix 1.K.1 we also look at the distribution of local market housing price volatility in detail. In contrast to idiosyncratic volatility, local market volatility is small and

29. Giacoletti (2021) studies local market risk at the zip-code level. Our definition of local markets relates to individual counties. The estimates of idiosyncratic risk that we obtain at the MSA level are, however, very similar to the ones we obtain at the zip code level for MSAs for which we have sufficient observations to use both approaches.

30. Note that this does not imply that city-wide factors are irrelevant for idiosyncratic housing risk. Realizations of sales-specific shocks are idiosyncratic by nature. But the distribution from which these sales-specific shocks are drawn is arguably the same for similar houses and will be determined by local housing market characteristics.

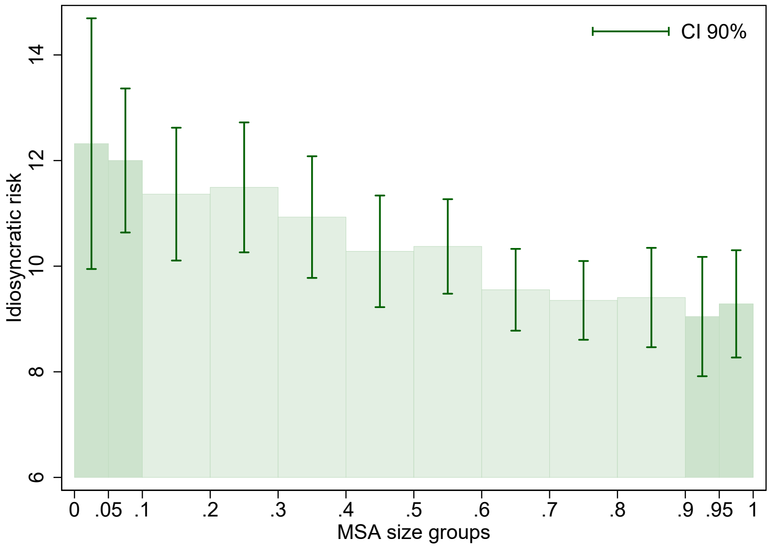

Figure 1.7. Annual idiosyncratic house price risk by MSA size, 1990-2020

Note: The figure shows average annual idiosyncratic house price risk for different MSA size groups for the period between 1990 and 2020. MSAs are divided into bins based on the size of MSA population in 1990. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half. All series are real and annualized.

does not differ significantly across MSAs. As such, we focus our discussion here on idiosyncratic volatility.

1.5.3.2 Idiosyncratic risk and housing market liquidity

The real estate finance literature has established a close relation between idiosyncratic risk and illiquid markets. Empirical work by Giacoletti (2021) and Sagi (2021) shows that matching frictions in housing markets (i.e. liquidity) drive the magnitude of idiosyncratic risk.[31] A close link between liquidity and idiosyncratic risk has also been shown for other asset classes, e.g. private equity.[32] We would thus expect that MSAs with large idiosyncratic housing price volatility also have very illiquid housing markets. In the next subsection, we test this prediction.

We look at evidence from two liquidity measures across MSAs in the U.S.: time on the market (TOM) and asking price discount. TOM measures the number of days

31. More precisely, they show that the idiosyncratic volatility is mostly realized at the points of sale and re-sale of the property.

32. Robinson and Sensoy (2016) show that most of the variation in cash-flows is idiosyncratic and Sorensen, Wang, and Yang (2014) demonstrate that idiosyncratic risk (non-systematic risk) faced by private equity investors arises due to its illiquidity. Furthermore, Mueller (2010) and Ewens, Jones, and Rhodes-Kropf (2013) provide empirical evidence that private equity funds with higher idiosyncratic risk also have higher expected returns.

between the original sale listing of a house and its actual sale. The asking price discount measures the difference between the original asking price and the final transaction price. Intuitively, in more liquid markets sellers will have to wait less time to sell (low TOM) and will be able to sell their properties for a price closer to the original asking price (low discount).

Table 1.8. Differences in mean and standard deviation of housing liquidity, US, 2012-2020

	Asking Price Discount (in p.p.)		
Sample	Mean	S.d. across time	N
Large vs rest	-0.87***(0.096)	-0.36***(0.016)	62688
Large vs small	-1.50***(0.184)	-0.75***(0.052)	6336
	Time on the Market (in days)		
Sample	Mean	S.d. across time	N
Large vs rest	-10.90*(6.184)	-4.34***(0.904)	26869
Large vs small	-29.67***(9.918)	-9.89***(1.782)	2716

Note: Note: Large MSAs are defined as being at or above the 95th percentile of the MSA population distribution in 2010. Small MSAs are defined as being at or below the 5th percentile of the MSA population distribution in 1950. Data are on the median number of days on Zillow and on the average discount to the asking price from Zillow.com for 277 MSAs for the period between 2012 and 2020. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

We use data from the online real estate marketplace *zillow.com* on median *time on zillow* and median *price cut* for 277 American MSAs for the last decade. Table 1.8 compares both measures of liquidity in the 5% largest MSAs with the other 95% and the smallest 5% MSAs. In the largest MSAs, sellers take significantly less time to sell on average. Table 1.8 states that the difference between the largest and the smallest MSAs is around 30 days, compared to an overall mean of 100 days. Not only is mean TOM significantly lower in large cities, but it also fluctuates significantly less over time. Results for the full MSA distribution can be found in Appendix 1.M.

The connection between idiosyncratic risk and housing market liquidity also implies that city-wide shocks – such as the often-cited decline of the car industry in Detroit – influence the distribution of sales-specific shocks. Van Dijk (2019) shows that housing liquidity dries up in declining housing markets. Our data also confirms that idiosyncratic risk in Detroit is far above other MSAs of similar size.[33] Moving beyond U.S. data, in Appendix 1.M we show that in Germany there are, on a per capita basis, more potential sales in larger cities and more potential buyers per sale.

33. The MSA *Detroit-Warren-Livonia* has an average annualized standard deviation of 13.30 percentage points, by far the largest in the largest size bin, which has an average standard deviation of only 8.35 percentage points and also far above Boston-Cambridge-Quincy (7.40) and Washington-Arlington-Alexandria (6.08), which had a comparable MSA size.

1.6 Conclusion

In our sample covering 27 cities in 15 countries we uncover a new stylized fact: superstar cities have persistently underperformed smaller, less dynamic cities in terms of housing returns. This result is puzzling given the well-established evidence that large agglomerations have witnessed substantially stronger housing price appreciation than the rest of the country in the last decades. Taking rental returns into account changes our understanding of the performance of housing assets across space. This new stylized fact reveals a second, equally important fact about housing markets: housing investments are significantly less risky in the larger agglomerations than in the rest of the country. In fact, these two new stylized facts interact in accordance with the prediction of a standard asset market rational expectations equilibrium: smaller and more risky locations have to offer higher expected housing returns in order to attract new capital. Rationalizing the spatial distribution of housing markets through the lens of an asset market equilibrium also represents, to the best of our knowledge, a novel type of approach, which could be very promising for spatial economics models more generally. Beyond the relevance for spatial economics, the large differences in housing returns across locations also emphasize the need to look more deeply into within asset-class return heterogeneity and its repercussions for wealth inequality dynamics and portfolio choice. We show that the choice between locations is strongly associated with different exposures to housing risk and returns and is, therefore, ultimately, a driver of wealth dynamics. The paper similarly invites more research on the importance of geography and size for the heterogeneity in returns on different assets.

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Appendix 1.A Additional data analyses - Market segmentation

Do housing prices and returns differ between different segments of the market? For a number of large German cities, we can draw on the full sample of transaction prices since the start of post-war records to compute house price indices (Osswald do Amaral et al. (2023)). Figure 1.A.1 shows the hedonic indices based on the full micro-data for Berlin, Cologne, Hamburg and Dusseldorf, each time for single-family houses (SFH), multi-family houses (MFH) and apartment transactions separately. The Figure shows common trends over time.

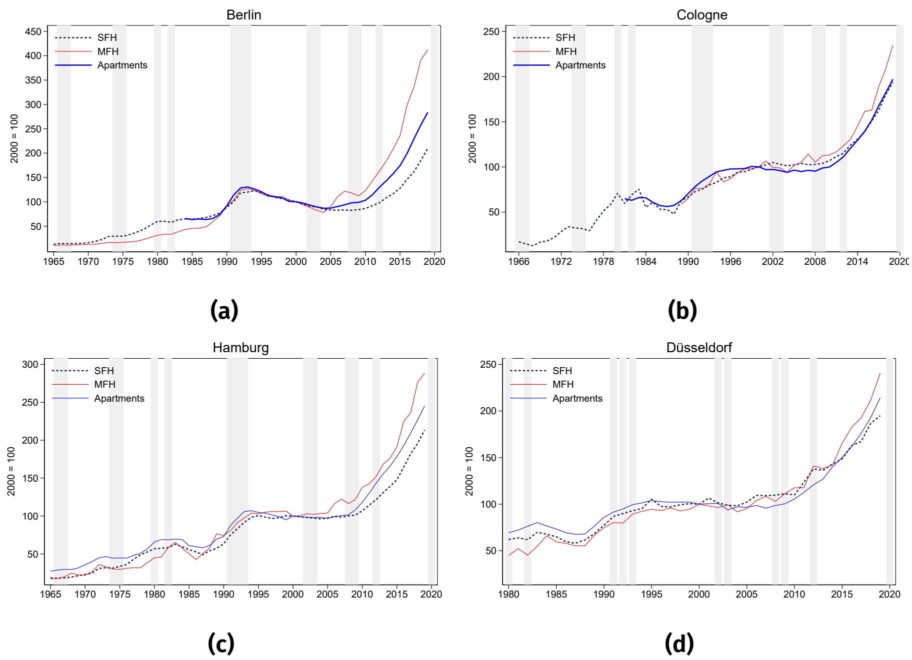


Figure 1.A.1. Housing price indices for different market segments and cities

Note: Hedonic house price indices for different housing types constructed from transaction level data.

Appendix 1.B Local CPIs

For a subsample of cities, we were also able to collect the city-level CPIs as published as regional break-down by national statistical offices. The local CPIs of different cities are displayed jointly with the respective national CPI by country in log scale in Figure 1.B.1. The comparison shows that the differences between CPIs of different cities within a country and their differences with the national CPI are negligible.

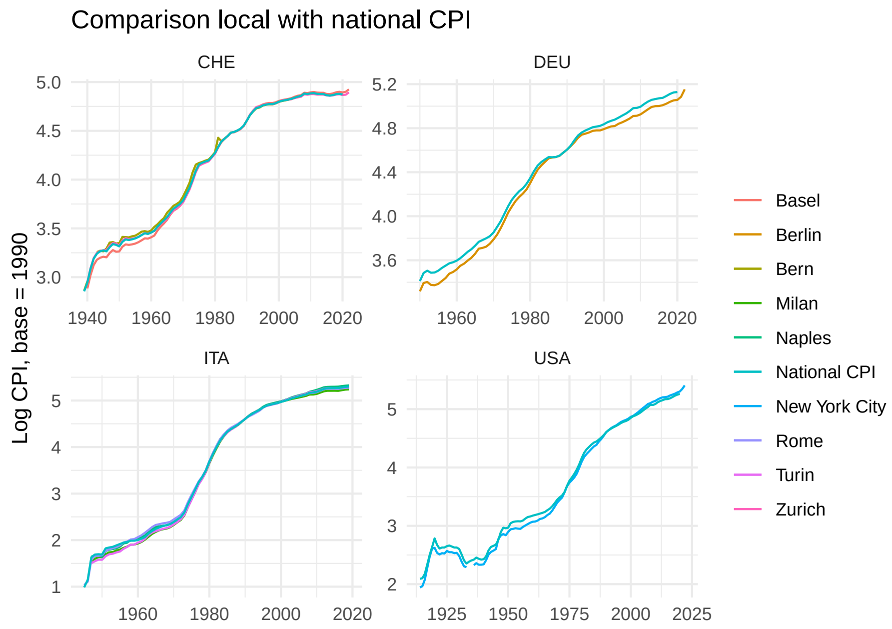


Figure 1.B.1. City-level CPIs in comparison with national CPI

Note: CPIs are logged with 1990 being the reference year. National CPI data are from Jordà, Schularick, and Taylor (2017)

Appendix 1.C Additional results for city vs national comparison

Table 1.C.1. Difference in yearly housing returns (log points) by cities, 1950-2018

City	Capital gain	Rent return	Total return	N
London	0.83 (0.81)	-1.78*** (0.17)	-0.95 (0.83)	68
New York	0.60 (1.45)	-1.96*** (0.08)	-1.36 (1.43)	68
Paris	0.38 (0.79)	-1.17*** (0.11)	-0.74 (0.78)	68
Berlin	2.99** (1.15)	0.83*** (0.23)	3.65*** (1.16)	56
Tokyo	-1.99 (1.96)	0.77*** (0.24)	-1.10 (1.93)	59
Hamburg	0.21 (0.67)	-0.57*** (0.09)	-0.36 (0.67)	56
Naples	0.14 (1.11)	-0.73*** (0.08)	-0.59 (1.10)	68
Barcelona	-0.66 (1.97)	-0.75*** (0.15)	-1.38 (1.93)	68
Madrid	-0.63 (1.93)	-0.97*** (0.19)	-1.59 (1.90)	68
Amsterdam	0.26 (0.98)	-0.22 (0.15)	0.05 (0.95)	68
Milan	2.23 (1.62)	-2.21*** (0.10)	-0.01 (1.61)	68
Melbourne	0.05 (0.77)	-1.42*** (0.08)	-1.35* (0.76)	68
Sydney	0.39 (0.79)	-1.02*** (0.08)	-0.63 (0.77)	68
Copenhagen	0.88** (0.44)	-3.14*** (0.18)	-2.22*** (0.49)	68
Rome	0.01 (1.15)	-2.93*** (0.08)	-2.88** (1.14)	68
Cologne	0.22 (1.43)	-0.26** (0.11)	-0.05 (1.42)	56
Frankfurt	0.09 (1.65)	-0.25* (0.13)	-0.16 (1.63)	56
Turin	-0.23 (1.09)	-1.23*** (0.07)	-1.44 (1.07)	68
Stockholm	0.04 (0.98)	-2.84*** (0.20)	-2.77*** (0.99)	68
Oslo	-0.11 (0.72)	-3.13*** (0.18)	-3.18*** (0.75)	68
Toronto	0.64 (0.75)	-2.51*** (0.34)	-1.86** (0.85)	62
Zurich	1.19 (1.47)	-0.59*** (0.07)	0.57 (1.44)	68
Gothenburg	0.23 (0.14)	-0.83*** (0.13)	-0.61*** (0.18)	68
Basel	1.51 (1.33)	-0.40*** (0.07)	1.06 (1.32)	68
Helsinki	0.63*** (0.24)	-4.04*** (0.29)	-3.39*** (0.34)	68
Vancouver	1.56 (1.20)	-2.68*** (0.36)	-1.15 (1.26)	62
Bern	0.15 (1.71)	-0.40*** (0.09)	-0.25 (1.68)	68

Note: The table shows the mean difference between city-level and national log housing returns, log capital gains and log rent returns by city. Standard errors (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

1.C.1 Differences in nominal returns

In this section, we present results regarding nominal returns. An important aspect of our baseline analysis is the potential influence of the CPI series on the results. Therefore, in this section, we replicate the main analysis using nominal return data.

The results are displayed in Table 1.C.2, and they confirm that all the key findings remain robust when using nominal series.

Table 1.C.2. City-level and national yearly nominal housing returns (log points), 1950-2018

	27 large cities			Only largest city/country		
	Cities	National	Difference	Cities	National	Difference
Capital gain	6.29	5.87	0.42* (0.23)	6.58	6.19	0.39 (0.29)
Rent return	3.55	4.94	-1.39*** (0.04)	3.51	5.20	-1.69*** (0.06)
Total return	9.63	10.53	-0.90*** (0.23)	9.87	11.08	-1.21*** (0.29)
N	1767			993		

Note: The table shows averages of city-level and national log nominal capital gains, log rent returns and log nominal housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

1.C.2 Splitting the sample into Europe and the rest of the world

In this section, we perform our main analysis from section 1.3.1, but we split our sample into a European sample and a non-European sample. Since our sample has a disproportionate amount of European cities we do this analysis to show that our results are not being driven solely by the European cities in our sample. In practice, this means that the non-European sample includes the United States, Canada, Australia and Japan. We report the results for both samples on Table 1.C.3. The Table shows that our results are both present in Europe as well as outside Europe.

1.C.3 Long-run comparison: Large cities vs. national portfolios

In this section, we repeat our main analysis from section 1.3.1, but extend the series for selected cities and countries backwards. We select all cities, for which we have long-run series and where the national housing series have a wide geographical coverage, even before 1950. The period before 1950 was characterized by large shocks such as wars and the Great Depression as well as fundamentally different housing policies, which were changing more rapidly and drastically compared to the postwar period. Although this describes a fundamentally different setting compared to today, we want to demonstrate that our results are robust even when including this time period.

A severe problem for this analysis is that, for many countries, the geographical coverage of the housing series in Jordà et al. (2019) is limited before World War II. As national statistical agencies were not in existence for most countries, the authors had to rely on housing series from other sources, which often only covered some or even just one large city. As our aim is not to compare our large cities to other (or

Table 1.C.3. City-level and national yearly housing returns (log points), 1950-2018

	Europe				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.34	1.86	0.48* (0.27)	1.66	0.68** (0.29)
Rent return	3.54	4.90	-1.36*** (0.05)	5.14	-1.60*** (0.05)
Total return	5.79	6.67	-0.87*** (0.27)	6.72	-0.93*** (0.29)
N	1380				
	Rest of the world				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	1.94	1.70	0.23 (0.49)	1.54	0.39 (0.59)
Rent return	3.60	5.09	-1.49*** (0.11)	5.44	-1.84*** (0.12)
Total return	5.47	6.71	-1.24** (0.49)	6.91	-1.43** (0.59)
N	387				

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

in fact often the same) large cities, we exclude all countries before 1950 that have a geographical coverage of house price or rent series of only a very small number of large cities. After matching with our city-level data, this leaves us, before 1950, with Germany starting 1925,[34] Norway starting 1891, the United Kingdom starting 1930[35] and the United States starting 1920.[36]

The results adding the large cities within these countries before 1950 are depicted in Table 1.C.4. For the sample of all 27 large cities, the results become, if anything, even stronger than when only including the data post 1950 in section

34. We start in 1925 to exclude the period of German hyperinflation, for which measurement of real house price and rent development is subject to very high uncertainty and data is missing for some cities. Moreover, national data for Germany is missing during and in the aftermath of World War II (1939-1962).

35. We have to exclude World War II (1939-1946) because national data is missing.

36. We needed to exclude a considerable number of countries because of narrow geographical house price coverage. From the remaining countries we exclude Italy, France and Switzerland, because the rent series before World War II only cover Milan, Paris and Zurich, respectively. Additionally, we exclude Australia because rent return series for the national Australian portfolio are subject to significant uncertainty before 1950, as can be seen in the Online Appendix of Jordà et al. (2019), and are moreover implausible compared to the housing series for Sydney and Melbourne from Stapledon (2007, 2012), which we use in our main data set. Housing return series start one year later, such that we are able to calculate capital gains with the wide coverage for all included countries. We provide a table with a precise description of the geographical coverage of the national series in the Data Appendix.

Table 1.C.4. City-level and national yearly housing returns (log points), long-run

	27 large cities			Only largest city/country		
	Cities	National	Difference	Cities	National	Difference
Capital gain	2.15	1.72	0.43* (0.24)	2.39	1.98	0.41 (0.30)
Rent return	3.61	5.11	-1.50*** (0.04)	3.69	5.39	-1.70*** (0.06)
Total return	5.67	6.75	-1.08*** (0.24)	5.98	7.27	-1.29*** (0.30)
N	1920			1039		

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. All 27 large cities are included after 1950. Before 1950, we add Berlin, Hamburg, Cologne, Frankfurt (all after 1925), Oslo (after 1891), London (after 1930) and New York (after 1920). The left-hand panel shows the results averaged over all 27 large cities in our main data set. The right-hand panel shows the results only for the cities that had the largest population in their respective countries in 1950 in our data. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

1.3.1. For the sample of only the largest city per country, the results stay virtually unchanged. This demonstrates that our results are not dependent on starting in 1950 and excluding the period featuring larger shocks to the housing market. Of course, as we still include the full sample after 1950, the weight on the observations before 1950 is small. However, if we instead include only the cities within countries with data coverage before 1950, the absolute differences in total housing returns stays virtually unchanged, but is less precisely measured.[37]

All in all, our main results do not depend on starting our comparison in 1950. Instead, the results become somewhat stronger when we include the time period before 1950 for countries with wider geographical coverage. As the data quality is, however, in general not as good as for the post-war period and large shocks like wars are a source of strong measurement error, we prefer the specification shown in the main text.

1.C.4 Comparison of housing returns over time

To demonstrate that our main result is not driven by specific time periods, we depict the difference between city-level and national housing portfolios over time.

37. The difference in total returns is -0.98** for all large cities in the respective countries and -1.14** for only the largest city per country. As the number of observations is considerably smaller in this specification, the results are, however, less precisely measured. The full results for this comparison are available on request.

As we want to minimize the effect of housing cycles, we compute 10 year lagged moving averages of this average difference.[38]

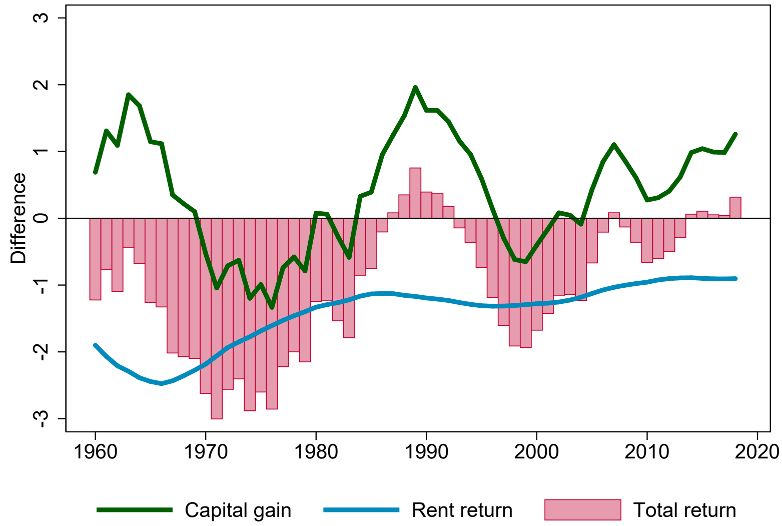


Figure 1.C.1. Average differences in city-level and national returns (log points) over time, 1950-2018

Note: This graph shows 10 year lagged moving averages of the mean difference in log capital gains, log rent returns and log total returns between the city-level and the respective national housing portfolios. The return period covered is 1951 to 2018, such that the moving averages start in 1960, except for the German cities, Tokyo and Toronto, because the national data starts later for these cities.

The outcomes are plotted in Figure 1.C.1. It shows that the main result is prevalent over time. The difference in rent returns is stable and negative over the entire time period. The difference in capital gains, in contrast, is more volatile and it is still possible to spot the influence of housing cycles. In consequence, the difference in total returns is also volatile, but negative during most periods.

1.C.5 Rent regulation

1.C.6 Analysis of outliers

In this subsection of the appendix, we repeat the main analysis of the paper while excluding outliers from our housing return series. Both positive and negative outliers in our city-level housing return series are primarily driven by significant swings in capital gains. To ensure that these outliers do not unduly influence our main results, we redo the main analysis while excluding different sets of outliers.

38. We rely on the results of Bracke (2013), who shows that the mean duration of complete housing cycles in 19 OECD countries between 1970 and 2010 was around 10 years.

Table 1.C.5. Difference in yearly housing returns (log points) by rent regulation, 1950-2018

Sample	Capital gain	Rent return	Total return	N
Weak rent reg.	0.52* (0.30)	-1.64*** (0.08)	-1.11*** (0.30)	497
Strict rent reg.	0.47 (0.44)	-1.74*** (0.08)	-1.26*** (0.44)	687

Note: The table shows the mean difference between city-level and national log housing returns, log capital gains and log rent returns. Standard errors (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. The first row shows the results for weak national rent regulations defined as a rent law index below one third, the second row the results for strict national rent regulation with a rent law index of at least two thirds. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Firstly, we address the largest outliers in our sample, which are caused by extremely large jumps in our city-level housing price series. We exclude housing returns above 40% and find a total of 19 cases falling into this category. The results can be found in Table 1.C.6. The main result of this paper, showing that large cities underperform the rest of the country in terms of total returns, becomes even more pronounced. The national series now outperforms the largest cities by 118 basis points per year, while in the main analysis, the difference was 95 basis points. This outcome is logical since we are excluding periods in which the largest cities experienced very large capital gains. As a result, the positive difference in capital gains between the largest cities and the national series becomes smaller and even non-significant.

Furthermore, to ensure that these large capital gains are not merely due to noise or data anomalies, we have gathered additional quantitative and qualitative evidence to support our series. In section 5.2 of the Data Appendix, we provide a paragraph for each one of the outliers, citing sources and presenting additional evidence that corroborates the validity of our findings.

Secondly, to ensure that we consider the impact of negative outliers as well, we repeat the main analysis by excluding all city-level total housing returns falling within both the top 5% and bottom 5% of the distribution. The results can be found in Table 1.C.7. The main findings of the paper remain robust and statistically significant. We confirm that large cities underperform in terms of total returns, even though they tend to overperform in terms of capital gains.

Table 1.C.6. City-level and national yearly returns without positive outliers, 1950-2018

	27 large cities				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	1.96	1.76	0.20 (0.23)	1.60	0.61** (0.26)
Rent return	3.54	4.94	-1.40*** (0.04)	5.21	-1.65*** (0.05)
Total return	5.43	6.62	-1.18*** (0.23)	6.73	-1.29*** (0.25)
N	1754				
	Only largest city/country				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.12	2.02	0.10 (0.29)	1.93	0.46 (0.34)
Rent return	3.51	5.17	-1.66*** (0.06)	5.42	-1.88*** (0.07)
Total return	5.56	7.09	-1.53*** (0.29)	7.25	-1.69*** (0.32)
N	1052				

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. Rest of country (RoC) returns are calculated as national housing portfolio returns share after taking out the returns of the 27 national large cities. We use previous year population shares as weights of the portfolio share of our cities, such that the estimate should be interpreted a lower bound. All city housing returns at or above 40% have been excluded from this analysis. The upper panel shows the results averaged over all 27 cities in our main data set. The lower panel shows the results only for the cities, which had the largest population in their respective countries in 1950 in our data. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 1.C.7. City-level and national yearly returns without positive and negative outliers, 1950-2018

	27 large cities				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.38	1.91	0.47*** (0.18)	1.74	0.61** (0.26)
Rent return	3.55	4.95	-1.41*** (0.04)	5.23	-1.65*** (0.05)
Total return	5.85	6.77	-0.92*** (0.18)	6.88	-1.03*** (0.20)
N	1595				
	Only largest city/country				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.63	2.15	0.48** (0.23)	2.03	0.46 (0.34)
Rent return	3.51	5.19	-1.68*** (0.06)	5.44	-1.88*** (0.07)
Total return	6.05	7.23	-1.18*** (0.24)	7.37	-1.31*** (0.27)
N	947				

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. Rest of country (RoC) returns are calculated as national housing portfolio returns share after taking out the returns of the 27 national large cities. We use previous year population shares as weights of the portfolio share of our cities, such that the estimate should be interpreted a lower bound. All city housing returns at or above 95th or at or below 5th percentiles of the distribution have been excluded from this analysis. The upper panel shows the results averaged over all 27 cities in our main data set. The lower panel shows the results only for the cities, which had the largest population in their respective countries in 1950 in our data. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Appendix 1.D Taxes

Taxes associated with real estate have a direct impact on the returns to housing and it is, therefore, important to take them into account when comparing returns across cities. To make this point clearer, consider the housing return equation, where we specifically account for taxes:

$$\text{Total return}_t = \frac{(P_t - P_{t-1})(1 - \tau_t^{capital})}{P_{t-1}} + \frac{R_t^{gross}(1 - \tau_t^{income} - \tau_t^{property})}{P_{t-1}}, \quad (1.D.1)$$

where $\tau_t^{capital}$ is the tax rate on capital gains, τ_t^{income} is tax rate on rental income, $\tau_t^{property}$ is the property tax rate paid by the owner and R_t^{gross} is the rent net of utility and maintenance costs, but not taxes.

If the tax incidence is systematically lower in smaller cities, this - rather than higher pre-tax returns - could explain why we do not find a premium for large cities. For this to be the case, the small-city tax advantage would need to exceed the size of the small city premium.

As mentioned in Section 1.2 we used data on net operating income yields from MSCI to benchmark our rent return series following the same procedure as in Jordà et al. (2019). MSCI defines the net operating income as being net of property taxes. Therefore, our results with the main data set are not driven by differences in property taxes between large and small cities. Nevertheless, we do not take into account capital gains and rental income taxes in the construction of our series for the main data set. Here we provide suggestive evidence that this omission in the construction of our series is not driving our main results.

1.D.1 Rental income & capital gains taxes

From Sections 1.3.1 and 1.4 we know that the largest cities have higher capital gains, but lower rental returns than the small cities. Therefore, if rental income is taxed considerably more than capital gains, then, post-taxes, the large city negative premium could disappear. Unfortunately, a precise measurement of the effective tax rates is extremely complicated, since these tax classes are often associated with partial or even full exemptions.[39] Nevertheless, we can still explore the fact that in the post-World War II period a great number of the countries in our sample tried to promote home ownership by reducing the tax burden on homeowners. Through the introduction of mortgage interest deduction and the abolition, or considerable decrease, of capital gains and imputed rents taxes, governments tried to incentivize

39. For example, landlords can deduct a substantial amount of property maintenance costs from the rental income taxes in the US and other countries in our sample. In Germany homeowners are exempted from capital gains taxes if they have owned the property for more than 10 years.

home ownership. Since, throughout this period, rental income continued, in most cases, to be taxed as normal income, this could lead to an effective higher tax burden on rental incomes as compared to capital gains. To test whether this was actually the case we used the series constructed in Kholodilin et al. (2023) to identify the combinations of countries and periods in which capital gains taxes, mortgage interest deductability or imputed rents taxes were effective. We then divided our sample into different sub-samples depending on the degree to which the tax system was effectively incentivizing home ownership or not. More precisely, we created the following three sub-samples: (i) "not pro homeowner" where only one of the three instruments was in place, (ii) "medium pro homeowner" where two of the instruments were in place and (iii) "strong pro homeowner" where all three instruments were in place. We then compared the return differences between the cities in our sample and the respective countries. The results can be seen in Table 1.D.1. In all three subsamples, the average returns in the largest cities remain significantly below the returns in the rest of the country.

Table 1.D.1. Difference in yearly housing returns (log points), 1950-2018

Sample	Capital gain	Rent return	Total return	N
Not pro homeowner	0.03 (0.40)	-1.13*** (0.07)	-1.09*** (0.40)	859
Medium pro homeowner	0.90*** (0.31)	-1.66*** (0.06)	-0.76** (0.31)	683
Strong pro homeowner	0.84*** (0.26)	-1.74*** (0.06)	-0.90*** (0.26)	840

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. The left-hand side shows the results averaged over all cities in our main data set. The right-hand side shows the results for the cities, which had the largest population in their respective countries in 1950. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Firstly, it is important to note that unlike property taxes, which have to be paid to the local government where the property is located, rental income and capital gains taxes can also depend on the homeowner's income and, as a result, these taxes do not necessarily have to be paid to the local government where the property is located. Additionally, landlords and homeowners can usually deduce property costs from the rental income taxes and in some countries capital gains are only taxed in the case of short-run holding periods. All these factors make it extremely complicated to have a precise estimate of within country variations in rental income and capital taxes.

Property taxes in the US data set

In the United States, the American Community Survey (ACS) provides detailed information on aggregate tax income generated by property taxes and the estimated tax values of homes on the county or even Census tract level. Contrary to other countries whose tax assessment values are far from market values, the US property tax is levied on a regularly assessed value of the underlying property and is thus partially a capital gains tax imposed every year. The average effective tax rate expresses the tax expenses as percentage of the average home value which can differ widely even within counties.

Figure 1.D.1 shows for tax data from the pooled 2010-2014 surveys that larger counties and larger MSAs have slightly larger effective tax rates. This suggests that returns in the largest MSAs in our US data set are disproportionately affected by taxes, with the difference in post-tax returns between large and small MSAs becoming even bigger than the difference in pre-tax returns.

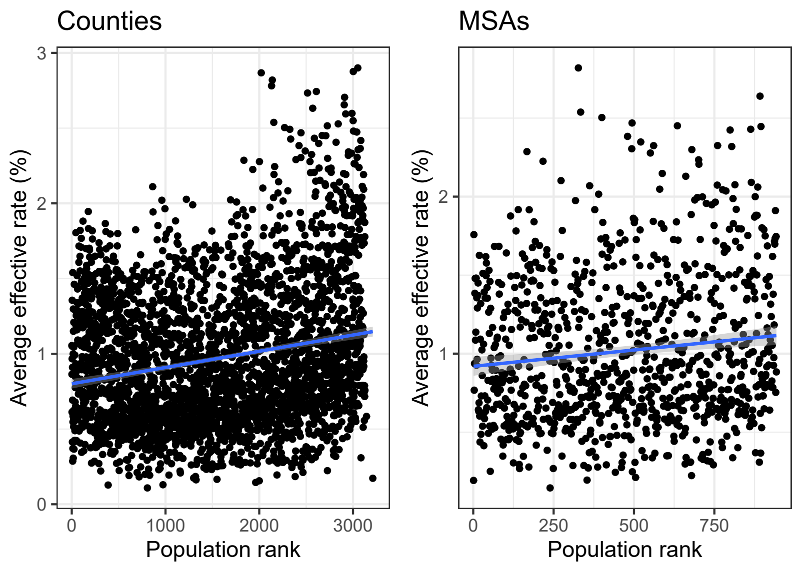


Figure 1.D.1. Effective property tax rates (percent) in counties and MSAs, 2010-2014

Note: The figure plots the relation between the average effective rate (in percent) for the period between 2010 and 2014 for the universe of U.S. counties (left) and U.S. MSAs (right). The sources of the are described in the text.

Appendix 1.E Returns across U.S. MSAs - statistical power

In this section of the appendix, we provide additional empirical evidence that supports the results indicating that the largest Metropolitan Statistical Areas (MSAs) in the U.S. have underperformed the rest of the market in terms of total housing returns. We conducted the regression analysis underlying the main result 10,000 times, each time randomly selecting a group of 15 MSAs to compare them to the rest of the market. Here, we present the distribution of the resulting coefficients and p-values and compare them to the coefficients and p-values of the 15 largest MSAs versus the rest. Please note that in all figures, the corresponding coefficient or p-value for the 15 largest MSAs is marked in red. Regarding p-values, we observe a similar pattern for total returns, rental returns, and capital gains. We find a uniform distribution between 0 and 1, indicating that statistical significance is not concentrated in one part of the distribution. As for the coefficients, we observe two distinct patterns. For total returns and rental returns, it is evident that the coefficient for the largest 15 MSAs clearly falls outside the distribution, confirming the robustness of our results. However, for capital gains, we observe that the coefficient lies within the distribution of coefficients for the randomly selected MSAs. While we find, on average, higher capital gains in the largest cities, statistically, this result does not appear as robust as the differences in returns and rental yields. This can be attributed to the considerable volatility of capital gains over time, making statistical inferences more complex. Nonetheless, the finding that large cities have experienced greater price appreciation over time has been demonstrated in other papers, which increases our confidence in our results (**gyourko2013**; Van Nieuwerburgh and Weill, 2010).

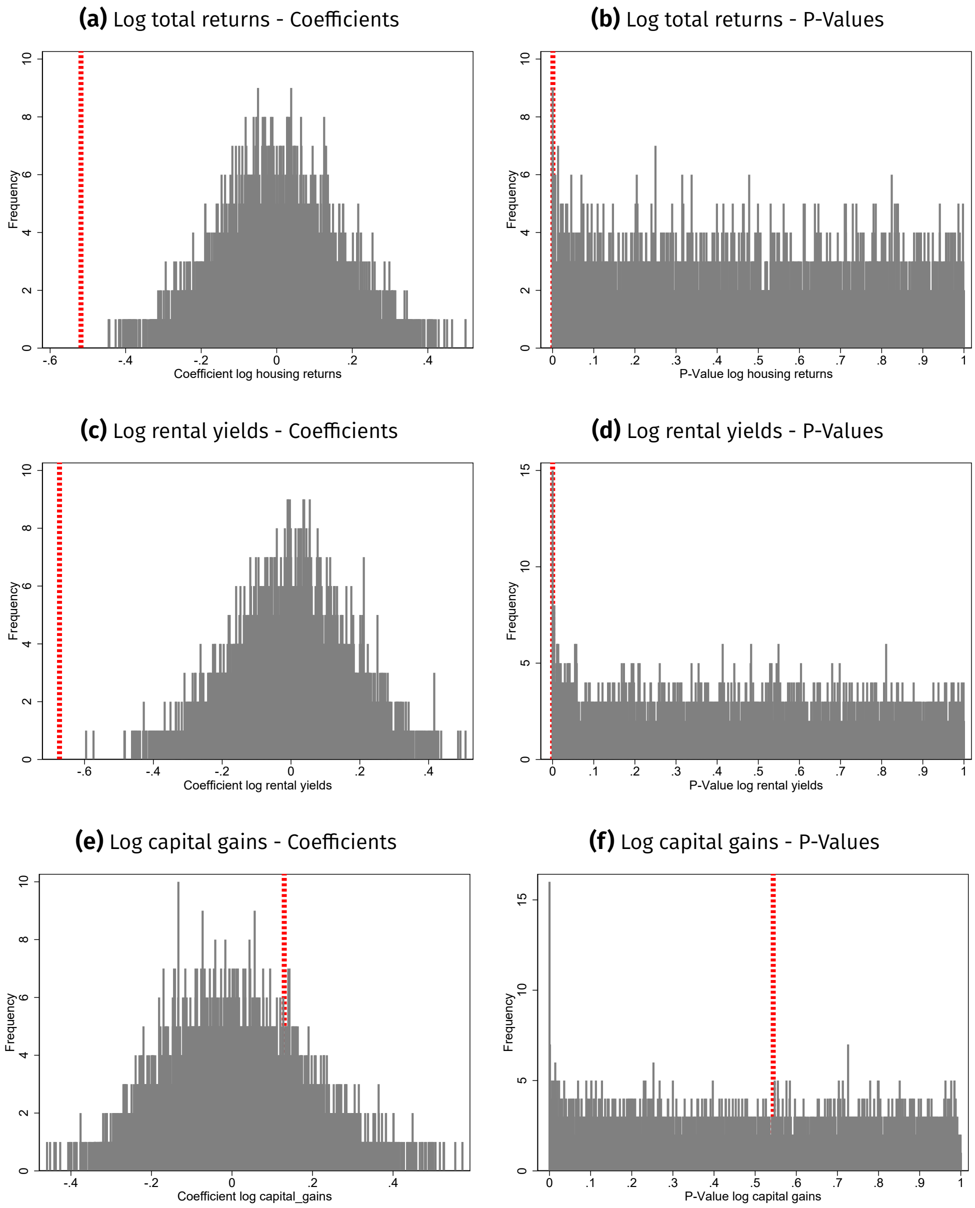


Figure 1.E.1. Distribution of coefficients and p-values for 10.000 random samples

Note: The Figures in the first column show the distribution of the coefficients and respective P-Values of 10.000 regression on 15 random MSAs. Additionally, the coefficient and corresponding P-Value for the 15 largest MSAs as in the baseline regression in Table 1.5 are shown in red.

Appendix 1.F Supply elasticity and MSA population

In this section of the Appendix, we delve into a more detailed examination of the connection between housing supply and the size of cities. Specifically, we use data on housing supply elasticities at the MSA-level from Saiz (2010) and merge it with MSA population data from the U.S. census. The supply elasticity measure from Saiz (2010) combines both geographical as well as regulatory constraints. Subsequently, we examine whether larger cities exhibit more inelastic housing markets. The findings are presented in Figure 1.F.1, where a binned scatter plot is depicted based on regressing housing supply elasticity against the population of the MSAs. The results are unequivocal: the big MSAs have significantly more inelastic housing supply.

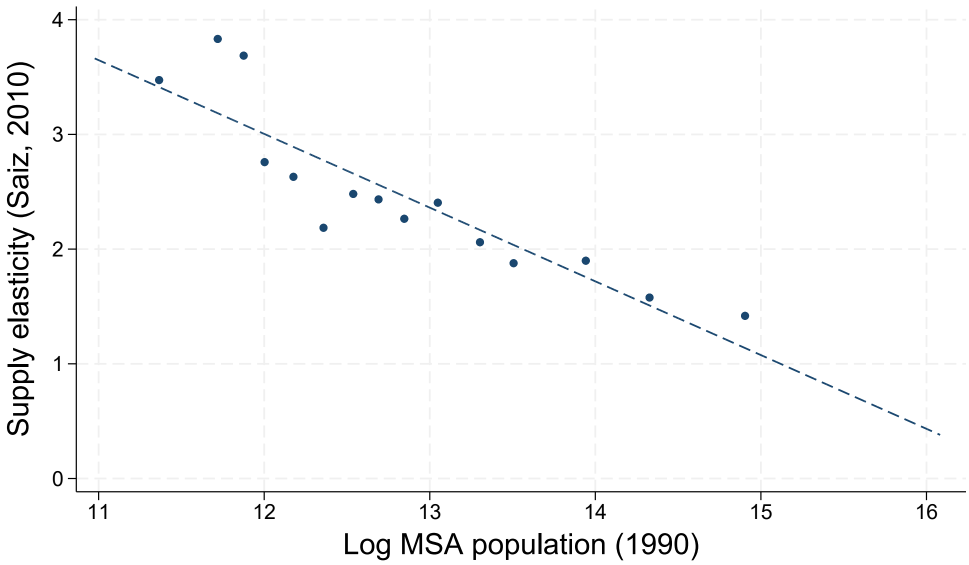


Figure 1.F.1. Supply elasticity and MSA population size, U.S.

Note: This Figure plots a binned scatter plot based on regressing housing supply elasticity on population at the MSA-level. The supply elasticity data is taken from Saiz (2010) and the population data is from the U.S. population and housing census of 1990.

Appendix 1.G Vacancy rates across the MSA size distribution

In this section of the appendix, we investigate whether vacancy rates vary across the housing quality distribution and whether this relationship is influenced by the size of the MSAs. Using the data from the American Community Survey, as described in Section 1.4 of the paper, we first split the MSAs into 10 different size categories base on the population of the MSAs in 2020. We first identify the least expensive census tract in each MSA and then calculate the mean, the maximum and the minimum of the rental vacancy rate within each MSA population category. The results can be found in Table 1.G.1. From the Table it is clear that the least expensive census have vacancy rates which are relatively small and there is not a clear pattern across the MSA population deciles. While the least expensive census tract with the highest rental vacancy rate in the smallest MSAs had a vacancy rate of 17.3%, some of the largest MSAs had census tract with more than 30% vacancy rates.

Table 1.G.1. Rental Vacancy rates in least expensive census tract by MSA population, 2010

Statistic	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
max	17.3	16.1	6.2	13.4	14.9	17.6	16.7	20.8	32.7	10.4
mean	8.1	8.0	2.9	4.1	8.2	6.6	6.6	8.0	19.6	2.5
min	0.0	1.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Note: The table shows average, maximum and minimum across the least expensive census tract by MSA population deciles. The columns represent the different MSAs population deciles. The first decile is P1 and includes all MSAs with a population below the 10th percentile of the MSA population distribution in 2020.

Nevertheless it could still be the case that within the smallest MSAs the least expensive census tracts had much higher vacancy rates than the more expensive census tracts. To test this for each MSA population category, we regress the rental vacancy rate in census tract i of MSA j in period t on the average housing value in the census tract in that period, p_{ijt}:

$$vacancy_{ijt} = \beta p_{ijt} + \alpha_j + u_{ijt} \tag{1.G.1}$$

where α_j are MSA fixed effects and the standard errors are clustered at the MSA level. We do this exercise for the year 2010 and 2020, as for these years we could use the 5-year ACS estimates, which are based on substantial more data than the 1-year estimates. In Figure 1.G.1, we present separate plots for the coefficient on the housing value for the years 2010 and 2020. Observing the figures, we find that the coefficient is positive and significant for the small MSAs and becomes very close to zero and even negative in the larger MSAs. Thus, there is no clear pattern in the data indicating a truncated distribution of rents in smaller cities. To ensure that our results are not being driven by census tracts, which are mostly composed of owner-occupied housing and, thus, have very low rental vacancy rates, we conducted a

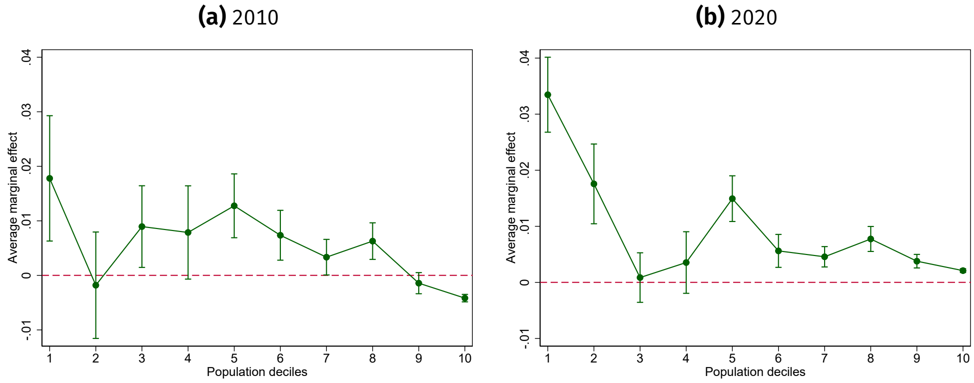


Figure 1.G.1. Housing value on rental vacancy rate by MSA population deciles

Note: Figure shows the coefficient β from equation 1.G.1 for each population decile, which are sorted in ascending order with population decile 10 containing the 10% largest MSAs by 2020 population.

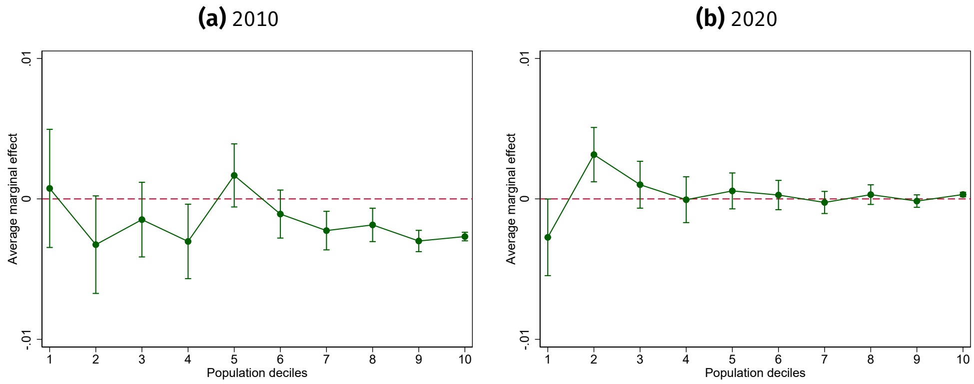


Figure 1.G.2. Rental value on rental vacancy rate by MSA population deciles

Note: Figure shows the coefficient β from equation 1.G.1 for each population decile, which are sorted in ascending order with population decile 10 containing the 10% largest MSAs by 2020 population.

similar analysis using rental value as a measure of the housing stock quality. The results of this analysis can be found in Figure 1.G.2.

In this alternative approach, we investigated the relationship between rental value and vacancy rates. We did not find a strong correlation between rental value and vacancy rates, as the relationship was not statistically significant different from zero for almost all size deciles.

Appendix 1.H Population and average housing prices

In this section of the appendix, we examine the correlation between our measure of city size and the level of housing prices across cities. Utilizing decadal data on average housing values from the census between 1950 and 2018 and the pop-

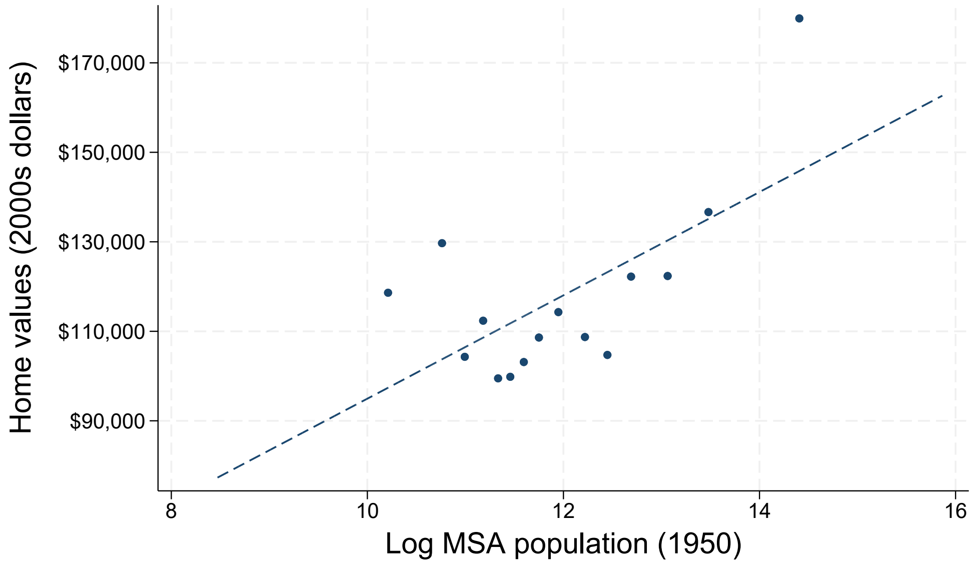


Figure 1.H.1. Housing prices and MSA population in 1950

Note: Figure is binned scatter plot based on a regression of housing value on population in 1950 at the MSA level, including year fixed effects. The regression is based on decadal data from the census between 1950 and 2018.

ulation by MSA in 1950, we present the results of a binned scatter plot in Figure 1.H.1, incorporating year fixed effects.

Appendix 1.I Spatial returns framework

In the following, we will focus on the rational expectations benchmark, but this is not meant to imply that behavioral factors are not important. Recent research has shown that behavioral factors matter in household decision making and home ownership decisions (for instance, Rozsypal and Schlafmann (forthcoming)). In our setting, it is possible that expectations for house price appreciation are systematically too optimistic in large cities, or that investors myopically focus on higher capital gains in the large cities and neglect the rent return component in total housing returns. In Appendix 1.J we use the framework of diagnostic expectations to explore the potential effects of behavioral biases (Bordalo et al., 2019).

In a rational expectation setting, we start with a parsimonious two-city model with housing investments in a large city A and a small city B. We assume that housing risk is lower in the large city A compared to the small city B. In an asset market equilibrium with rational expectations, risk-adjusted total returns need to equalize between cities, such that investors are indifferent between investing in city A or city B:

$$\left(\frac{R^A_{t+1}}{P^A_t} + cg^A_{t+1}\right) * \frac{1}{\delta^A} = \left(\frac{R^B_{t+1}}{P^B_t} + cg^B_{t+1}\right) * \frac{1}{\delta^B}, \tag{1.I.1}$$

with P^l_t being the house price at time t in location l, R the rent payment, and $cg^l = \frac{P^l_{t+1} - P^l_t}{P^l_t}$ the capital gain. δ^l is the location-specific discount rate. As housing risk is lower in city A, risk-averse investors will discount future payments in A at a lower rate than in B: $\delta_A < \delta_B \iff \frac{1}{\delta_A} > \frac{1}{\delta_B}$. This holds as long as investors have some degree of risk aversion and implies that, in order to attract investors, risky city B will need to offer higher housing returns than safe city A:

$$\frac{R^A_{t+1}}{P^A_t} + cg^A_{t+1} < \frac{R^B_{t+1}}{P^B_t} + cg^B_{t+1}. \tag{1.I.2}$$

For simplicity of exposition, we assume that houses in both cities feature the same expected future rental cash-flow: $R^A_{t+1} = R^B_{t+1}$. Note that the same will hold under the potentially more realistic assumption that future rents are expected to rise faster in the large city.[40] In order for the equilibrium condition (1.I.1) to hold, current prices will adjust. Investors will be willing to pay a higher price for the safer

40. This is because investors will be willing to pay a higher price for a house with the same *current* rental income, which leads to a lower rent return in city A.

rental cash-flow in the large city, because future payments are discounted at a lower rate. Rent returns will be lower in A compared to B:

$$\frac{R^A_{t+1}}{P^A_t} < \frac{R^B_{t+1}}{P^B_t}. \tag{1.I.3}$$

This helps rationalize the empirical finding (ii) that rent returns are lower in large cities. In a next step, we can rewrite inequality (1.I.2) as:

$$cg^A_{t+1} - cg^B_{t+1} < \frac{R^B_{t+1}}{P^B_t} - \frac{R^A_{t+1}}{P^A_t}, \tag{1.I.4}$$

which shows that, in equilibrium, the difference in rent returns between city B and city A will be larger than the difference in capital gains between A and B. This, in turn, would rationalize our third stylized fact that the difference in rent returns in favor of small cities exceeds the difference in capital gains between large and small cities.

While it is clear that the right-hand side of inequality (1.I.4) is larger than zero, this does not, however, pin down the difference in capital gains. It could be the case that risky cities have higher capital gains than safer cities or vice versa. Yet the empirical evidence clearly points to higher capital gains in large cities.

Appendix 1.J Housing return expectations

The theory of diagnostic beliefs, as described in Gennaioli and Shleifer (2018), provides a unifying framework, which accounts for the different behavioral biases, i.e. deviations from rational expectations theory, that were documented in the finance and economics literature. It states that people form expectations by extrapolating from past experiences and by overweighting specific representative patterns in the data they observe. Representativeness is defined in the sense of Tversky and Kahneman (1983): "an attribute is representative of a class ... if the relative frequency of this attribute is much higher in that class than in a relevant reference class". In other words, some patterns in the data are more salient than others and, therefore, their importance is overvalued. This theory has found empirical support not only in stock return expectations (Bordalo et al., 2019), but also in macroeconomic expectations, such as for consumption or investment (Bordalo et al., 2020). In these cases, forecasters are shown to extrapolate from past trends in the data and to overreact to macroeconomic news. There has not been an explicit attempt to study housing markets from the lens of diagnostic beliefs, but most studies investigating behavioral biases in house price or return expectations find evidence for extrapolation. Expectations of future house price growth are strongly correlated with recent house price appreciation (see e.g. Kuchler and Zafar (2019), De Stefani (2020) or Case, Shiller, and Thompson (2014)), and expectations causally affect future housing investment decisions (see Armona, Fuster, and Zafar (2018) or Bailey et al. (2018)). Therefore, we will use this framework to organize our discussion on potential biases in housing return expectations.

The housing literature (e.g. Gyourko, Mayer, and Sinai (2013)) and section 1.3.1 have shown that large "superstar" cities have outperformed the rest of their countries in terms of house price appreciation. Moreover, media coverage and the public debate in recent years seem to have focused on the strong house price growth in specific cities, for example concerned about the resulting affordability problems. Recent research by De Stefani (2020) shows peoples' perceptions about the local house price evolution depend on past local price growth. This could potentially explain why homebuyers are more optimistic about the future of the housing markets in large cities than in smaller cities or rural areas and, therefore, willing to pay a higher house price today. In addition, it might be plausible that homebuyers overweight the capital gains component of total returns over the rent return component. We know from section 1.3 that rent returns represent the majority of housing returns, still most news about the housing market focuses exclusively on the evolution of house prices and not on rent returns.[41]

41. One reason might be the fact that house price data over time is more readily available than rent data.

From the perspective of diagnostic beliefs, capital gains are a good candidate for being a representative heuristic of total housing returns, since they are more salient than rent returns. Combining extrapolation of past house price growth and overweighting of the capital gains component has the potential to explain why housing return expectations could be differentially biased between large cities and the rest of the country. If this bias is persistent over time, this could, in turn, explain why house prices in large cities are elevated and, consequently, housing returns are smaller than in other cities as observed in the data.[42]

For illustration, we take the extreme assumption that discount rates are non-stochastic and equal between cities, such that we can drop them from equation 1.I.1. Next, we assume that expectations are formed using past average capital gains and rent returns, but placing a different weight on the capital gain component, such that we can rewrite the equation as:[43]

$$w^P \ast \overline{cap\ gain}^A + \overline{rent\ return}^A = w^P \ast \overline{cap\ gain}^B + \overline{rent\ return}^B, \tag{1.J.1}$$

where w^P is the subjective weight that homebuyers attach to capital gains. We know that capital gains in the large city A have been higher on average than in the small city B, $\overline{cap\ gain}^A > \overline{cap\ gain}^B$. If $w^P > 1$, then the expected returns would increase relatively more in the large city A compared to B. As a result, the expected discounted returns in city A and B could equalize holding discount rates constant across both cities.

Unfortunately, to the best of our knowledge, data on housing return expectations is scarce, let alone on a regional level. Existing surveys mostly focus on house price developments only and are only representative on the national level.[44] Therefore, we are not aware of a direct way to test this hypothesis. However, with a back of the envelope calculation, we are able to approximate the subjective capital gain weight (w^P) that would be necessary for equation 1.J.1 to hold in equilibrium over

42. There is, however, evidence that the effect of expectations on house prices depends on the level of interest rates (Adam, Pfäuti, and Reinelt, 2020) and might, therefore, not be persistent over time. Periods of low interest rates can lead to larger fluctuations in expectations-driven house price dynamics.

43. Here we also make the assumption that extrapolation of past house price growth is constant across cities. There is evidence that sentiment plays a larger role is local housing markets with a higher share of less-informed buyers (Soo, 2018). Nevertheless, there is no clear evidence on the relation between sentiment and expectations.

44. Although there are some more detailed surveys on housing, e.g. the National Housing Survey from Fannie Mae or the Michigan Survey of Consumers, which contain questions on price and rent expectations, these neither allow approximating rent return expectations directly, as price-rent ratios are missing and questions are not very specific, nor do they feature enough observations to reliably approximate expectations on a city-/MSA-level.

our long-run data. In the comparison between large cities and national housing portfolios in section 1.3.1, the resulting weight on capital gains would approximately need to be 2.35.[45] This implies that home-buyers would need to attach more than double the weight (or attention) to capital gains than to rent returns, when forming their expectations about future housing returns. Consequently, a substantial behavioral bias would be necessary to explain spatial differences in housing returns without any differences in discount rates.

For homebuyers planning to become owner-occupiers a considerable bias in housing return expectations might, however, be probable. These types of buyers might neither have a reliable estimate of the rent a potential property would be able to earn nor pay much attention to future rent growth. For large-scale (e.g. institutional) real estate investors, in turn, who buy houses or apartments to rent them out, a large behavioral bias seems to be less realistic. Due to their investment strategy, these types of investors can be assumed to take rent returns into account and not overweight capital gains to a large extent. Still, we observe that large real estate investors are concentrated in the largest cities, although housing returns have been lower in these cities on average. Preqin data show that city size is an important predictor for how many real estate deals and residential housing value changed hands in big deals among institutional investors in Europe in the 2010s.[46] At least for these expert homebuyers, a rational explanation seems to be more likely.

Our main results focus on the mean differences in housing returns between large and small cities over a long time period. Deviations from rational expectations in housing markets found in the literature, e.g. extrapolative expectations, have been established over the housing cycle. In that sense, the theory of diagnostic beliefs is more appropriate to explain the cyclical behavior in housing markets. Since we would expect the biases in beliefs to correct over a sufficiently long time period, we propose an alternative rational explanation for the mean differences in returns.

45. To calculate the weight on capital gains we first transform the log returns from Table 1.3 into percentage returns, because log returns do not aggregate linearly across return components. By assuming that capital gains weights are constant across cities and countries, we can then simply calculate the necessary weight for the differences to be equal to 0. For our main specification (*Cities vs National*) we calculate a subjective capital gains weight of 2.35.

46. Results are available on request.

Appendix 1.K Estimation of idiosyncratic risk

In this section we describe in more detail the method we used to estimate idiosyncratic risk. Like we mentioned in section 1.N, we mostly follow the method employed by Giacoletti (2021).

Before analyzing the results, it is important to note that our estimation differs from the one in Giacoletti (2021) in two ways. First, we are not able to explicitly take remodeling expenses into account, as the necessary data is missing. However, as shown by Giacoletti (2021), remodeling expenses mainly affect the mean and not the standard deviation of the sales specific shock, which is our variable of interest. Secondly, we do not explicitly control for physical characteristics of housing, since these are absent from the data we use. Nevertheless, our estimates of idiosyncratic risk for the MSAs in California are very similar to the ones in Giacoletti (2021). Therefore, we do not think that these limitations influence our city-level comparisons.

We define the local market at the county level. To measure house prices at the county level, we build new house price indices from January 1990 to December 2020 combining repeat-sales indices from FHFA, which cover the period between 1990 and 1996, and price indices from Zillow.com, which cover the period after 1996. The FHFA indices are built based on single-family transactions covered by mortgages guaranteed by Fannie Mae or Freddie Mac.[47] The Zillow Home Value Index is based on *zestimates* for single-family houses. *Zestimates* are quality-adjusted house price estimates, constructed using proprietary algorithms that incorporate data on sales and listings prices and other home and transaction characteristics from a variety of sources.[48]. We then aggregate the county level indices to the msa-level using repeat sales transaction weights from the Corelogic data set.

Following Giacoletti (2021) we combine the county level series with the corelogic transaction level data to construct the Local Market Equivalents (LME). LMEs measure the extent to which a specific house re-sale deviates from the value fluctuation of the median house in the same county. They are computed as follows:

$$LME_t = \frac{P^{loc}_{i,t_i} - P_{i,t_i}}{P_{i,t_i}}; \qquad P^{loc}_{i,t_i} = \frac{P_{i,T_i}}{R^{loc}_{t_i,T_i}}, \tag{1.K.1}$$

where P_{i,T_i} is the nominal price at which the house was sold, P_{i,t_i} is the price at which the house was initially bought and R^{loc} is the gross capital gain on the local County price index, i.e. $R^{loc}_{t_i,T_i} = \frac{Index_{county_i,T_i}}{Index_{county_i,t_i}}$. P^{loc}_{i,t_i} is then the market-adjusted buying

47. More details regarding the methodology used to produce the series are described in Bogin, Doerner, and Larson (2018).

48. More details about the data and methodology can be found in *www.zillow.com*

value of the house.

The changes in individual house values can also stem from transaction and house characteristics, which are more prevalent in specific MSAs. Therefore, in a second step, we remove the additional return variation determined by common house and transaction characteristics from the individual house resale value fluctuations. For that purpose we run the following regression:

$$\tilde{lme}_i = \alpha_{s,y} + \alpha_{e,y} + \alpha_{s,m} + \alpha_{e,m} + \alpha_{zip} + \beta_P log(P_{i,t_i}) + BX_i + u_i, \tag{1.K.2}$$

where $\tilde{lme}_i = \frac{lme_i}{\sqrt{hp_i}}$ and hp_i is the holding period in years. The rescaling by holding periods follows Sagi (2021) and deals with potential collinearity arising from differences in holding periods across resales. $\alpha_{s,y}$ and $\alpha_{e,y}$ are fixed effects for the year in which the house was bought and sold,$\alpha_{s,m}$ and $\alpha_{e,m}$ are fixed effects for the month in which the house was bought and sold and α_{zip} is a zip-code fixed effect. $log(P_{i,ti})$ is the log of the price at which the house was bought, which is also a control for other unobservable persistent characteristics. BX_i is a vector of additional transaction characteristics. The vector X_i contains dummies for different holding periods (less than 2 years, between 2 and 3 years, between 3 and 5 years, between 6 and 8 years, between 8 and 10 years and longer than 10 years), it also contains dummies for sales or resales which fit the following descriptions: short sales, bought solely with cash, foreclosures, and bought or sold by institutional investors or real estate developers. [49]

The residuals u_i then capture the unexplained component of returns, which is controlled for systemic price fluctuations and common house and transaction characteristics. We then measure annual idiosyncratic risk as the standard deviation of the residuals within a specific MSA. The standard deviation in measured in terms the original price's %. Since the dependent variable of the regression is scaled by the square root of the holding period we need to rescale the residual as $\hat{e}_i = \hat{u}_i \sqrt{hp_i}$ in order to have the residual associated with the holding period.

We also do a comparison of the standard deviation of the residuals across MSAs. The results can be seen in the second row of Table 1.K.1, which can be found in Section 1.K.1. Larger MSAs have a lower idiosyncratic risk than smaller MSAs.

1.K.1 Distribution of house price growth variation

Table 1.K.1 shows annual total house price growth variation and its decomposition across the MSA-size distribution for the period between 1990 and 2020. Following Giacoletti (2021), we define total house price growth variation as the sum

49. For a full description of the methodology please refer to Giacoletti (2021).

Table 1.K.1. Total house price growth variation and its decomposition by MSA size, 1990-2020

	1A	1B	2	3	4	5	6	7	8	9	10A	10B
Local risk	4.96	5.02	5.65	5.14	5.19	5.16	5.46	5.79	5.51	5.09	6.58	6.63
Idiosyncratic risk	12.32	12.00	11.36	11.49	10.93	10.28	10.37	9.55	9.35	9.41	9.05	9.29
Share of idios. risk	0.81	0.83	0.76	0.80	0.78	0.76	0.76	0.72	0.73	0.75	0.64	0.65
Total risk	13.61	13.17	13.11	12.80	12.47	11.86	12.18	11.64	11.18	10.96	11.54	11.63
# Repeat sales	139369	126863	266186	359600	406745	616257	732470	1038956	1532555	3003841	3190250	4779689
# MSAs	13	12	25	25	24	25	25	24	25	25	12	12

Note: All risk measures are yearly and in percentage points of initial prices. MSAs are divided into bins based on the size of MSA population in 1990. The bins go from the smallest MSAs (bin 1A) to the largest MSAs (bin 10B). The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half.

of idiosyncratic risk and local house price risk. We measure local house price risk as the standard deviation of the yearly growth of the local house price index. We divide the 248 MSAs into increasing size bins according to their population in 1990. The first row shows that local risk increases slightly with MSA size. This finding might seem counter-intuitive at first glance,[50] but can be explained by the observation that large urban centers tend to have tighter housing supply constraints,[51] which amplify shocks to house prices leading to higher house price index volatility.[52] However, the differences are not statistically significant. Additionally, as shown in the last section, overall house price growth co-varies less with income in the largest MSAs.[53] Conversely, idiosyncratic risk is substantially smaller in the largest cities and clearly decreases with MSA-size.

Next, we look at total house price risk. As idiosyncratic house price risk represents the major share of total house price risk across the entire MSA-size distribution (Row 3), the pattern of idiosyncratic risk across MSAs is reflected in the distribution of total risk. Consequently, Row 4 of Table 1.K.1 reveals that total risk also decreases with MSA-size. While the smallest MSAs had on average an annual total house price risk of 13.61% of the sales price of a house between 1990 and 2020, the largest MSAs had a considerably lower total risk of 11.63% relative to the sales price.

50. This result is, however, not new, but has already been shown for example in Bogin, Doerner, and Larson (2018).

51. See, for example, Saiz (2010).

52. See Paciorek (2013) for a theoretical and empirical explanation of the relation between housing supply constraints and house price index volatility.

53. Moreover, tighter supply constraints imply that house price increases will be higher in reaction to positive demand shocks. As housing supply cannot be decreased easily in all cities, the effect of negative demand shocks will be much more comparable between constrained and unconstrained cities. Tighter supply constraints, therefore, are comparable to an option value for positive demand shocks without bearing a higher risk if demand shocks are negative.

Appendix 1.L Co-variance risk distribution and MSA-level betas

In this section we show that the co-variance between excess housing returns and income growth decreases almost monotonically across the city-size distribution. Next, we show that also MSA-level housing betas are lower for large cities.

Figure 1.L.1 plots the average co-variance between excess housing returns and income growth by MSA-size group for the period between 1950 and 2018. We can see that the co-variance is significantly positive for the smallest MSAs, and decreases almost monotonically with MSA-size. For the largest MSAs the estimated co-variance is not significantly different from zero.

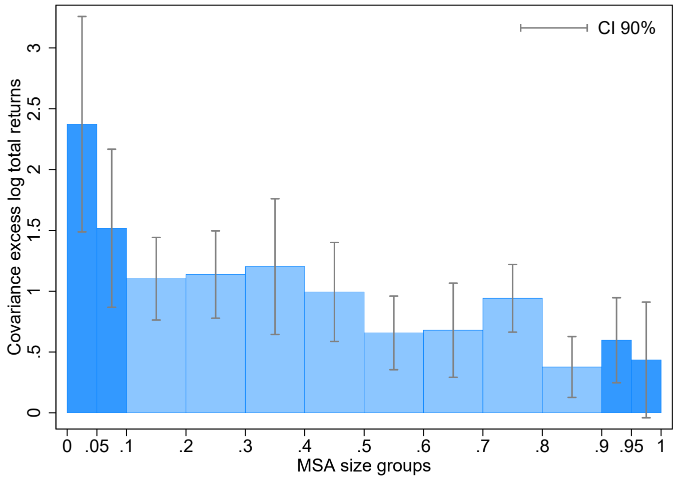


Figure 1.L.1. Co-variance between log excess total housing returns and log income growth by MSA size, 1950-2018

Note: The figure shows the co-variances for different MSA size groups for the period between 1950 and 2018. For clarity the co-variances are multiplied by 10,000 MSAs are divided into bins based on the size of MSA population in 1950. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half.

We calculate MSA-specific betas as:

$$\beta_s = \frac{Cov(R_s - R_f, y_s)}{Var(y_s)},$$

where R_s is total real log housing return for MSA s, R_f is total real log return on short-term US t-bills and y_s is average real log income growth in MSA s. We calculate income betas for the period between 1950 and 2018.[54] We then test whether

54. Note that given the decadal frequency of the data, we have overall 7 data points for each variable MSA combination.

income betas are smaller in large MSAs. The results are depicted in Table 1.L.1 column 3. It shows that income betas of total housing returns are indeed significantly smaller in large MSAs compared to the rest. The difference becomes larger when we compare the largest MSAs to only the smallest ones.

Table 1.L.1. Differences in income betas by city size, US, 1950-2018

Sample	Capital gain	Rental Yield	Total return	N
Large vs rest	-0.23*** (0.036)	-0.24*** (0.018)	-0.29*** (0.033)	2212
Large vs small	-0.57*** (0.079)	-0.35*** (0.032)	-0.66*** (0.073)	217

Note: The table shows differences in income betas for log excess total returns, log excess capital gains and log excess rental yields between large MSAs and the rest of the sample or small MSAs. Differences are measured as coefficients in a cross-sectional regression of the dependent variable (income beta) on a large MSA dummy. Robust standard errors in parenthesis. Large MSAs are defined as being at or above the 95th percentile of the MSA population distribution in 1950. The second row shows the same, but comparing large MSAs only to small MSAs, which are defined as being at or below the 5th percentile of the MSA population distribution in 1950. Overall, we use estimates for 316 MSAs between 1950 and 2018. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

We do the same analysis for the two components of log total returns: log capital gains and log rental yields. We calculate the income betas for each one of the components separately. The results can be found in Table 1.L.1 columns 1 and 2, which also show that betas for both components are smaller in the largest cities.

Table 1.L.2. Summary statistics by city size, US, 1950-2018

Variable	Statistic	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Housing returns	mean	5.698	5.460	5.441	5.553	5.467	5.405	5.263	5.369	5.252	5.063
Housing returns	sd	2.292	1.731	1.905	1.669	1.794	1.870	1.653	1.790	1.707	1.922
Capital gains	mean	1.822	1.586	1.567	1.417	1.390	1.501	1.332	1.432	1.474	1.716
Capital gains	sd	2.139	1.670	1.838	1.632	1.723	1.896	1.637	1.706	1.621	1.898
Rental yield	mean	3.947	3.933	3.932	4.191	4.131	3.961	3.980	3.990	3.832	3.400
Rental yield	sd	0.628	0.543	0.570	0.494	0.530	0.581	0.436	0.547	0.499	0.568
Income growth	mean	1.015	1.015	1.015	1.014	1.013	1.014	1.014	1.014	1.014	1.015
Income growth	sd	0.016	0.016	0.015	0.016	0.016	0.016	0.016	0.016	0.016	0.017

Note: The table shows the mean and standard deviation for the decomposition of housing returns and income growth by population deciles. Both housing returns and income growth are measured in annual log points corrected for inflation. P1 represents the MSAs in the lowest population decile, while P10 represents the MSAs in the top population decile.

Appendix 1.M Additional results on housing liquidity

US: Table 1.M.2 and Table 1.M.2 show the liquidity measures for the US over the entire city-size distribution.

Table 1.M.1. Cross-sectional differences of time on the market for 277 MSAs, 2012-2020

	1	2	3	4	5	6	7	8	9	10
mean	114.92	97.31	107.26	98.96	107.84	101.26	93.60	99.61	89.69	85.56
sd	39.37	27.72	29.42	30.54	32.51	27.81	26.55	26.98	24.86	25.69

Notes: MSAs are divided into decile bins based on the size of MSA population in 2010. Decile represents the 10% smallest MSAs. Each bin contains between 27 and 28 MSAs. Data on the median number of days on Zillow from Zillow.com for 277 MSAs for the period between 2012 and 2020.

Table 1.M.2. Cross-sectional differences of asking price discount in p.p. for 277 MSAs, 2012-2020

	1	2	3	4	5	6	7	8	9	10
mean	114.92	97.31	107.26	98.96	107.84	101.26	93.60	99.61	89.69	85.56
sd	39.37	27.72	29.42	30.54	32.51	27.81	26.55	26.98	24.86	25.69

Notes: MSAs are divided into decile bins based on the size of MSA population in 2010. Decile represents the 10% smallest MSAs. Each bin contains between 27 and 28 MSAs. Data on the average discount to the asking price from Zillow.com for 277 MSAs for the period between 2012 and 2020.

Germany: We analyze two liquidity measures for Germany, which are connected to the thickness of the housing market. Using data from the online real estate marketplace *immobilienscout24.de*, we test whether large cities in Germany have a stronger supply and demand for housing. We first look at the supply side by analyzing the number of sales ads posted per capita in each city. The results can be found in panel (a) of Figure 1.M.1. It shows that in larger cities there are significantly more ads posted per capita. This indicates that even on a per capita basis, housing supply is larger in large cities. We next quantify demand for housing. To do so, we look at the number of hits per sales ad by city. Figure 1.M.1 panel (b) shows that in large cities housing ads receive substantially and significantly more hits, and therefore have more potential buyers, than in small cities. This indicates that, even relative to a higher supply, demand per supplied unit is substantially larger in large cities.

The results based on German data are very insightful because they measure liquidity on a per sale or per capita basis. The fact that there are mechanically more sales and inhabitants in larger cities amplifies the effect. Other local housing market characteristics might additionally reinforce the link between larger liquidity and lower risk in large cities. For example, large cities might have more institutionalized

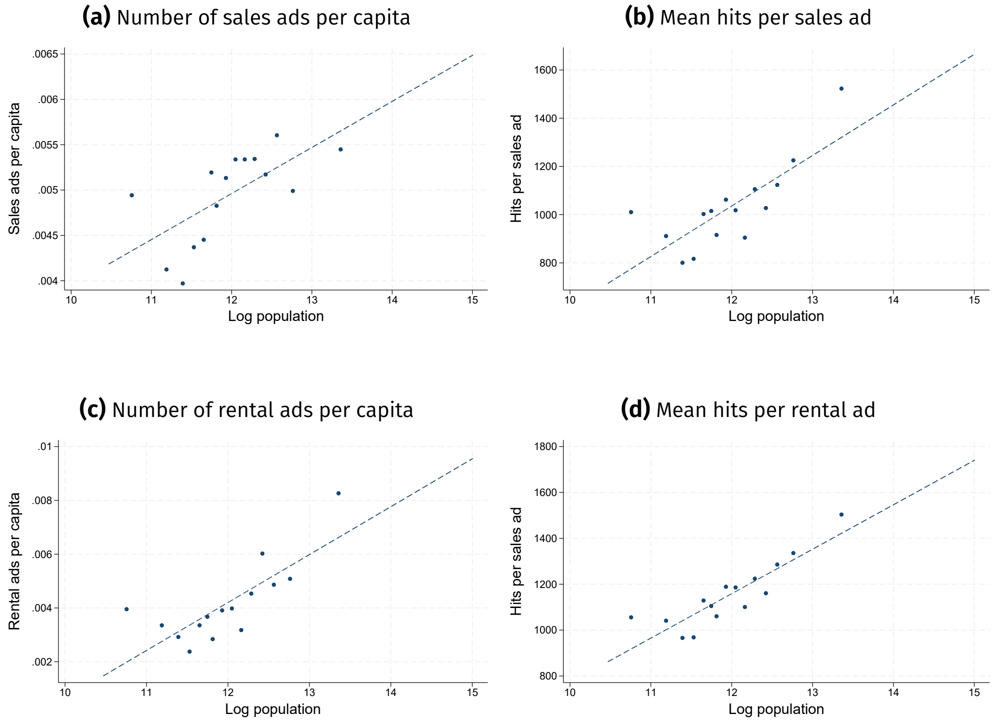


Figure 1.M.1. Thickness of the housing market by city size, Germany

Note: The figure displays four binned scatterplots of market thickness measures on city population in 2015 for 98 German independent city counties (*kreisfreie Städte*) between 2007 and 2019. The underlying regression includes year fixed-effects. The first row displays measures of market thickness based on apartment and single-family house sales ads. The second row displays measures of market thickness based on apartment and single-family house rental ads. All data is from the largest German listing website for real estate *ImmoScout24*. For details about the data source please refer to Klick and Schaffner (2020).

housing markets, which further reduce matching frictions and can make better use of the more abundant information from comparison prices.

Real estate liquidity of institutional portfolios in European cities

Finally, we document how the big real estate transactions, residential and total, as recorded by Preqin rather take place in cities of bigger size in European cities of the 2010s.

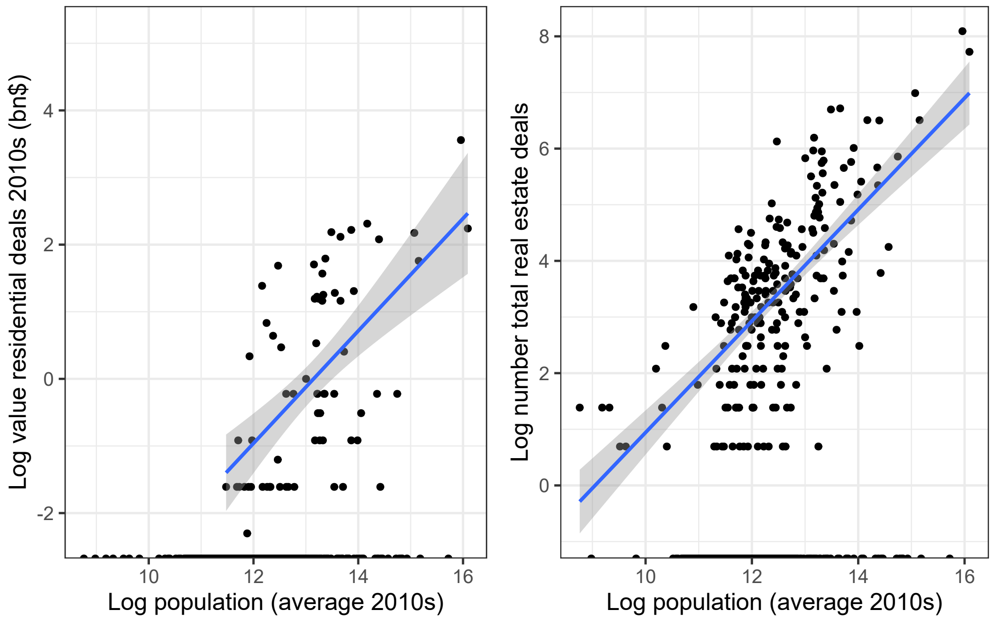


Figure 1.M.2. Liquidity of housing markets in European cities

Note: Preqin data for big deals of institutional investors, total sum since 2011 and Eurostat population data averaged for the 2010s.

Appendix 1.N Rental yield risk and city size

In this section, we provide evidence on spatial differences in rental yield volatility. Rental yields at the property level are defined as the rental income of a property divided by its potential sales price. Consequently, volatility in rental yields can have two possible sources: changes in rental income or changes in the sales price. Changes in rental yields driven by changes in the sales price are negatively related to changes in capital gains. To see why, consider the following simplified example: Assume a property at time t has a rental yield of 5%. At time $t+1$, its price doubles, but the rental income stays constant. This leads to a capital gain of 100 percentage points in t+1, but its rental yield is reduced to 2.5%, such that total returns only change by 97.5 percentage points. The negative co-variance between rental yields and capital gains at the property level attenuates capital gain volatility, but only to a small extent.[55]

The other source of rental yield volatility are changes in the rental income of a property. We can decompose volatility in rents in a location-wide and an idiosyncratic component. In the remainder of this section we show empirical evidence that

55. Eichholtz et al. (2020) also find a negative co-variance of rental yields and capital gains empirically.

suggests that, if anything, both components of rental income risk are lower in large cities.

First, we analyze location-wide rent risk. Unfortunately, there does not exist a data set with long-run annual rent data on city- or MSA-level for the U.S. However, the German data set we use in section 1.4.2 does feature rent indices for a large cross-section of German cities. We use these data to calculate location-wide rent volatility on city level. Figure 1.N.1 plots volatility in annual rent growth by city size. For both samples, one of 42 cities for the period between 1975 and 2018 (left hand side) and the other of 127 cities between 1993 and 2018 (right hand side), rent growth volatility is smaller in larger cities.

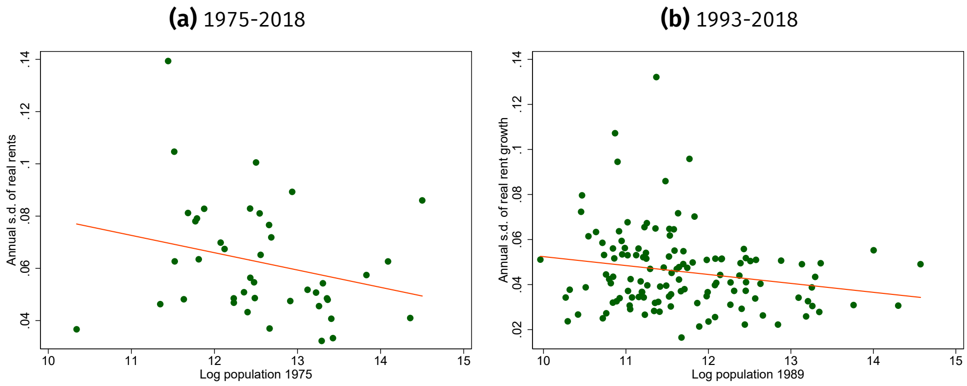


Figure 1.N.1. Real rent growth volatility and population, Germany

Note: Standard deviation of real rent growth for 42 German cities between 1975 and 2018 (Panel (a)) and for 127 German cities between 1993 and 2018 (Panel (b)). More details on the data sources can be found in the Data Appendix.

Next, changes in rental vacancies also induce volatility in rental income of a property. One the one hand, for a large-scale investor with a high number of rental units within a city, volatility of city-level vacancy rates add to location-wide rental income risk. On the other hand, for a small property owner with only one rental unit, a higher city-level vacancy rate induces a higher idiosyncratic risk, because it increases the probability that his one unit is vacant. We use data from the American Housing Survey from the period between 1985 and 2020 for 49 MSAs to compare vacancy rates between large and smaller MSAs. The results can be found in Table 1.N.1. It shows that the mean as well as the standard deviation of annual rental vacancies is lower in large cities.

Both pieces of evidence suggest that location-wide risk in rental income is smaller in large cities. Regarding idiosyncratic risk, the problem is that, to the best of our knowledge, no data set exists that covers rental income at the property level over a long-enough time period for a cross-section of cities. However, as we argue in section and is shown by Giacoletti (2021), Sagi (2021) and Kotova and Zhang (2019), idiosyncratic risk in capital gains is mainly driven by liquidity in the hous-

Table 1.N.1. Differences in mean and standard deviation of rental vacancies in p.p., US, 1985-2020

Sample	Mean	N	S.d.	N
Large vs rest	-2.06*(1.093)	1372	-0.73***(0.169)	1372
Large vs small	-1.25(1.415)	168	-1.06***(0.274)	168

Note: The Table shows the difference in rental vacancy rates between the 5% largest MSAs in terms of 1970 population relative to the other MSAs in the sample (Row 1) and to the 5% smallest MSAs (Row 2). The data covers 49 MSAs for the period between 1985 and 2020 and is collected from the American Housing Survey.

ing market. As the rental market is not fundamentally different from the house sales market, we also expect liquidity to play a considerable role for idiosyncratic risk of rental income. Unfortunately, we cannot use the liquidity measures for the US for the rental market that we use for the house sales market. However, we can replicate the two measures we use for liquidity in Germany also for the rental housing market. The second row of Figure 1.M.1 shows the results, which are, if anything, even stronger then for the house sales market and highly significant. This strengthens the assumption that idiosyncratic rental income risk is, if anything, smaller in large cities.

To summarize, the evidence presented in this section is only suggestive, because we cannot calculate rental yield volatility at the property level for a cross-section of cities. However, each piece of evidence points at a lower rental yield volatility in large cities compared to smaller ones. This suggests, that, if anything, including rental yields volatility would increase the risk differences between large and small cities.

Appendix 1.O Data appendix for 27 cities

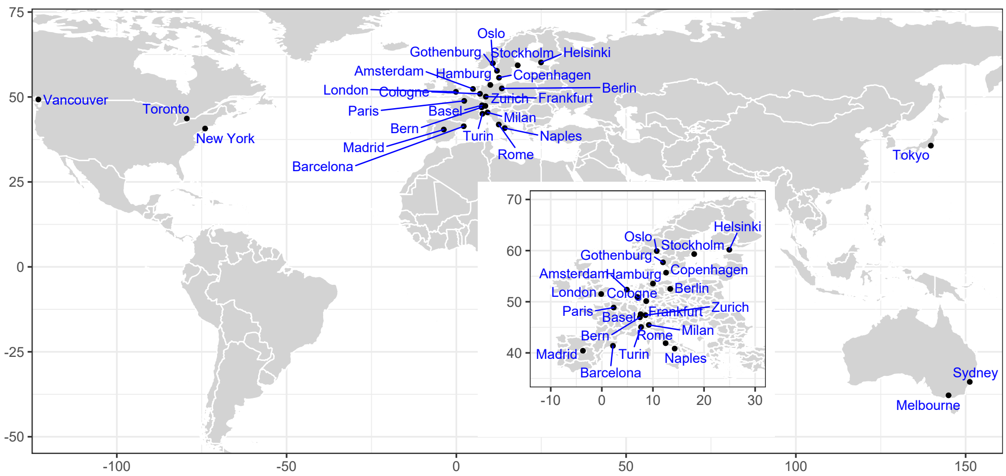


Figure 1.O.1. Geographical distribution of our city sample

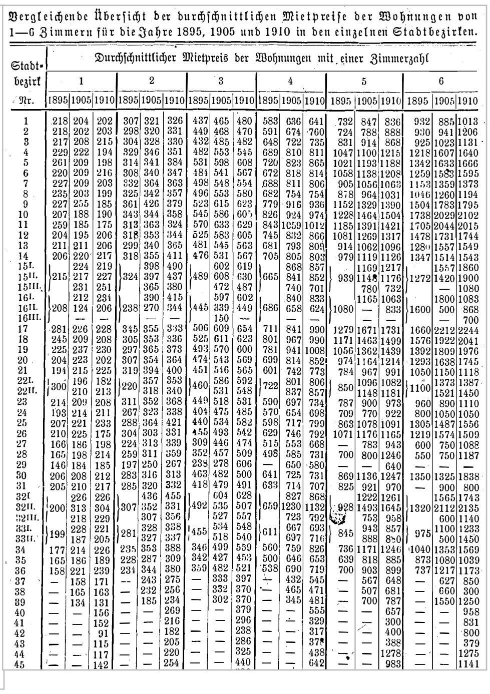
Note: Latitude and longitude are given on the y- and x-axis, respectively. The map was built using the shape file in Becker et al. (2018).

In this appendix, we describe the methods and sources used to build our new long-run city-level housing return data set.[56] Figure 1.O.1 shows the geographical distribution of the cities included in our sample. Table 1.O.1 displays an overview of the new series we constructed including the sources we used. We collected additional data on 20 out of our 27 sample cities; 13 of them had to be constructed from scratch. In the following, there is a subsection for every city, which are each divided into three parts. We first describe how we built the price series, then the rent series and, finally, the rental yield series. The focus of this section is on the sources and methods used in our final series, but we also provide an overview of alternative sources, whenever we know of their existence. As we mentioned in the text, we used the rent-price approach to build the rental yield series. This approach can lead to the accumulation of measurement errors over time. For this reason, we also show when and how we used historical benchmarks to correct our rental yield series.

56. Figure 1.O.2 panel (a) shows an example of the property ad section of the *Kensington Post* in 1965. The marked advertisements are used in our final index.

(a) London, 1965

(b) Frankfurt, 1895-1910



Vergleichende Übersicht der durchschnittlichen Mietpreise der Wohnungen von 1—6 Zimmern für die Jahre 1895, 1905 und 1910 in den einzelnen Stadtbezirken.

Stadt-bezirk	Durchschnittlicher Mietpreis der Wohnungen mit einer Zimmerzahl																	
	1			2			3			4			5			6		
Nr.	1895	1905	1910	1895	1905	1910	1895	1905	1910	1895	1905	1910	1895	1905	1910	1895	1905	1910
1	218	204	202	307	321	326	437	465	480	583	636	641	732	847	836	932	885	1013
2	218	202	203	298	320	331	449	468	470	591	674	760	724	788	888	930	941	1206
3	217	208	215	304	328	330	432	485	482	648	722	735	831	914	868	925	1023	1131
4	229	222	194	329	346	351	482	553	545	689	810	811	1047	1100	1215	1218	1607	1640
5	261	209	198	314	341	384	531	598	608	720	823	865	1021	1193	1188	1342	1633	1666
6	220	209	216	308	340	347	484	541	567	672	818	814	1058	1138	1208	1259	1583	1595
7	227	209	203	332	364	363	498	548	554	688	811	806	905	1056	1063	1153	1359	1373
8	235	203	199	325	342	357	496	553	580	682	754	754	878	964	1031	1046	1260	1194
9	227	255	185	361	426	379	523	615	623	779	916	936	1152	1329	1390	1504	1783	1795
10	207	188	190	343	344	358	545	586	605	826	924	974	1228	1464	1504	1738	2029	2102
11	259	185	175	313	363	324	570	633	629	843	1059	1012	1185	1391	1421	1705	2044	2015
12	204	195	206	318	353	344	525	583	605	745	832	866	1081	1269	1317	1478	1731	1744
13	211	211	206	299	340	365	481	545	563	681	793	809	914	1062	1096	1280	1557	1549
14	206	220	217	318	355	411	476	531	567	705	805	803	979	1119	1126	1347	1514	1543
15I.		224	219		398	490		602	619		868	857		1169	1217		1557	1860
15II.	215	217	227	324	397	437	489	608	630	665	841	852	939	1148	1176	1272	1420	1900
15III.		231	251		365	380		472	487		740	701		780	732		—	1080
16I.		212	234		390	415		597	602		840	833		1165	1063		1800	1083
16II.	208	124	206	238	270	344	445	339	449	686	658	624	1080	—	833	1600	500	868
16III.		—	—		—	—		150	—		—	—		—	—		—	700
17	281	226	228	345	355	333	506	609	654	711	841	990	1279	1671	1731	1660	2212	2244
18	245	209	208	305	353	336	525	611	623	801	967	990	1171	1463	1499	1576	1922	2041
19	225	237	230	297	365	373	493	570	600	781	941	1008	1056	1362	1439	1392	1809	1976
20	204	223	202	307	354	364	474	543	569	699	814	852	974	1164	1214	1293	1638	1745
21	194	215	225	319	394	400	451	546	565	601	742	773	784	967	991	1050	1150	1118
22I.	300	196	182	220	357	353	460	586	592	722	801	806	850	1096	1082	1100	1373	1387
22II.		210	213		318	340		531	548		837	857		1148	1181		1521	1450
23	214	209	208	311	352	368	449	518	531	590	697	734	787	900	973	960	890	1110
24	193	214	211	267	323	338	404	475	485	570	654	698	709	770	922	800	1050	1050
25	207	221	233	288	364	421	440	534	582	598	717	799	863	1078	1091	1305	1487	1556
26	210	225	175	304	303	331	455	493	542	629	746	792	1071	1176	1165	1219	1574	1509
27	166	186	198	224	313	339	309	446	474	515	553	668	—	783	943	600	750	1088
28	165	198	214	259	311	359	352	457	509	498	585	731	700	800	1246	550	750	1187
29	146	184	185	197	250	267	238	278	606	—	650	580	—	—	640	—	—	—
30	206	208	212	283	316	313	463	482	500	641	725	731	869	1136	1247	1350	1325	1838
31	205	210	217	285	320	332	418	479	491	633	714	707	825	921	970	—	900	800
32I.		226	226		436	455		604	628		827	868		1222	1261		1565	1743
32II.	200	313	304	307	352	331	492	535	507	659	1230	1132	928	1493	1645	1320	2112	2135
32III.		218	229		307	356		527	557		723	792		753	958		600	1140
33I.	199	228	221	281	328	338	455	534	548	611	667	693	845	943	857	975	1100	1233
33II.		187	205		327	337		518	540		697	716		888	850		500	1450
34	177	214	226	235	353	388	346	499	559	560	759	826	736	1171	1246	1040	1353	1569
35	165	186	189	228	287	309	342	427	453	500	646	653	639	818	885	873	1080	1039
36	158	221	239	234	344	380	359	482	521	538	690	719	700	903	899	737	1217	1173
37	—	158	171	—	243	275	—	333	397	—	432	545	—	567	648	—	627	850
38	—	165	163	—	232	256	—	332	370	—	465	471	—	507	681	—	660	300
39	—	134	131	—	185	234	—	302	370	—	345	481	—	700	787	—	1550	1250
40	—	—	156	—	—	269	—	—	379	—	—	555	—	—	657	—	—	958
41	—	—	152	—	—	216	—	—	296	—	—	329	—	—	300	—	—	831
42	—	—	91	—	—	182	—	—	238	—	—	317	—	—	400	—	—	800
43	—	—	115	—	—	205	—	—	286	—	—	378	—	—	388	—	—	379
44	—	—	117	—	—	220	—	—	325	—	—	438	—	—	1278	—	—	1275
45	—	—	142	—	—	254	—	—	440	—	—	642	—	—	983	—	—	1141

Figure 1.O.2. Examples of primary and secondary sources

Note: Panel (a): Extract of the real estate part of the ad section for the 14th of May 1965 from the newspaper *Kensington Post*. Panel (b): From *Beiträge zur Statistik der Stadt Frankfurt am Main 11. NF (1919)* published in Busch (1919).

Table 1.0.1. Overview of the new series

City	Series	Period	Source	City	Series	Period	Source
London	house	1946-1969	newspaper	Cologne	house	1966-2018	trans. records
London	rent	1946-1998	newspaper	Cologne	rent	1904-1972	stat. yearbook
Paris	house	1950-1958	newspaper	Cologne	rent	1973-2018	market reports
Berlin	house	1870-1964	stat. yearbook	Frankfurt	house	1897-1959	stat. yearbook
Berlin	house	1965-2018	trans. records	Frankfurt	house	1960-2018	trans. records
Berlin	rent	1870-2018	stat. yearbook	Frankfurt	rent	1895-1965	stat. yearbook
Tokyo	house	1950-1975	newspaper	Frankfurt	rent	1972-2018	market reports
Hamburg	house	1870-1970	stat. yearbook	Turin	house	1927-1996	stat. yearbook
Hamburg	house	1971-2018	market reports	Turin	rent	1927-1996	stat. yearbook
Hamburg	rent	1870-1966	stat. yearbook	Stockholm	rent	1894-2018	stat. yearbook
Hamburg	rent	1972-2018	market reports	Oslo	rent	1950-1970	newspaper
Naples	house	1927-1996	stat. yearbook	Toronto	house	1900-1991	newspaper
Naples	rent	1927-1996	stat. yearbook	Toronto	rent	1921-1991	newspaper
Barcelona	house	1960-2008	newspaper	Zurich	house	1905-2018	stat. yearbook
Milan	house	1956-1966	newspaper	Zurich	rent	1915-2018	stat. yearbook
Milan	house	1967-1996	stat. yearbook	Gothenburg	rent	1914-2018	stat. yearbook
Milan	rent	1950-1996	stat. yearbook	Basel	house	1912-1981	stat. yearbook
Rome	house	1927-1996	stat. yearbook	Basel	rent	1920-2018	stat. yearbook
Rome	rent	1914-1996	stat. yearbook	Bern	house	1912-2018	stat. yearbook
Cologne	house	1870-1965	stat. yearbook	Bern	rent	1915-2018	stat. yearbook

Note: This table lists all new series we constructed ourselves. Some of these series we had to construct from scratch, others were taken from contemporaneous statistical publications, which we combined to build long-run indices. More details about the sources and methods can be found in the rest of the Data Appendix.

Acknowledgements: We would like to thank the following persons and agencies for their very valuable contributions to the data collection process, without which this project would not have been possible:

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1.0.1 Australia

The six largest cities in Australia in 1900 were in descending order: Melbourne, Sydney, Adelaide, Brisbane, Newcastle and Ballarat. All of them encompassed more than one percent of the country population in 1900.[57] According to the algorithm described in the main paper, we took the two largest cities, Melbourne and Sydney, and then stopped, as we already covered more than 25 percent of the country's population in 1900. Long-run housing data are available for both cities. For the other cities, in contrast, long-run housing data are sparse.

1.0.1.1 Melbourne

House Price Series. Stapledon (2012) builds a long-run house price index for Melbourne for the period between 1880 and 2011. His index is based on real estate ads from the newspaper *Melbourne Age* until 1970. For the sub-period 1880–1943, the index is computed from the median asking price for all types of residential buildings, indiscriminate of their characteristics; for 1943–1949, Stapledon (2012) estimates a fixed price;[58] for 1950–1970, he uses the median sales prices from housing auctions, which were also reported in the newspaper *Melbourne Age* for this period.

For the post-1970 period, Stapledon (2012) uses both Abelson and Chung (2005) as well as Australian Bureau of Statistics (2020), which we explain in more detail below. Stapledon (2012) also discusses an existing historical asking price series for Melbourne from Butlin, which covers the period between 1861 and 1891 and that is consistent with his own series.

Abelson and Chung (2005) build a median house price index for Melbourne for the period between 1970 and 2003. For this series they rely on: (i) a 1991 study by *Applied Economics and Travers Morgan*, which draws on sales price data from the *Land Title Offices*, for the period between 1970 and 1979, and (ii) on sales price data from the Department of Housing, i.e. the *Victorian Valuer-General Office*, for the period between 1980 and 2003.

The *Australian Bureau of Statistics* (ABS) published a quarterly index for Melbourne for the period between 1986 and 2005 for i) established detached residential dwellings and ii) *project homes*, i.e. dwellings available for construction on a client's block, excluding land. The indices are calculated using a stratification method, where the transaction prices are stratified by geographical area and physical characteristics of the dwelling (Australian Bureau of Statistics, 1993).

Since 2004, ABS also publishes quarterly indices for Melbourne for i) established detached dwellings and ii) attached homes. They additionally publish a third

57. City-level population data are taken from Reba, Reitsma, and Seto (2016) and country-level population data from Jordà, Schularick, and Taylor (2017).

58. A 1943 law fixed nominal house prices in Australia to 1942 levels during this period. The house price freeze ended in 1949, which explains the strong jump in the series between 1949 and 1950.

index, which is an aggregation of the first two, which we use to construct our final Melbourne house price index. The indices are calculated using a stratification method. Locational, structural and neighborhood characteristics are used to mix-adjust the index, i.e. to control for compositional change in the sample of houses. Each quarter, the strata are re-valued by applying a price relative (i.e. the current period median price of the stratum compared to the previous period median price of the same stratum) to the value of the dwelling stock for that stratum to produce a current period stratum value. The series are constructed as Laspeyres-type indices. Sales price data are taken from the State Valuer-General Offices and is supplemented by data on property loan applications from major mortgage lenders (Australian Bureau of Statistics, 2018).

Table 1.O.2 summarizes the main components of our final house price index. From 1880 to 1970 we rely on the index by Stapledon (2012), because it is the only long-run index and, as mentioned above, correlates very strongly with the other existing indices for the overlapping periods. We then splice the index from Stapledon (2012) with the one from Abelson and Chung (2005) for the period between 1970 and 1986. Abelson and Chung (2005) discuss all existing indices for this period and their choice of final index is based on the representativeness of the underlying data. From 1986 onward, we use the indices produced by the Australian Bureau of Statistics, because these are the only available indices, which adjust for quality and compositional changes by applying a stratification index methodology. This is the only period where our series differs from the one in Stapledon (2012).

Rent Series. Stapledon (2007) builds a rent index for Melbourne between 1901 and 1954 using adjusted rent estimates for census years (1911, 1921, 1933 and 1947). The estimates are the weighted average of gross rents of tenant-occupied dwellings and the imputed rents of owner-occupied dwellings. The imputed rents are calculated using a 20% premium. These estimates are interpolated using the national CPI rent component from ABS. Whenever the average change between the estimated census years is higher or lower than the change in the national rent index, the author adjusts his results proportional to the difference between rent index rate of change and average change between census data points.

To the best of our knowledge there does not exist a rent index for Melbourne for the period between 1955 and 1972. To fill this gap, we collected data on average weekly rent for tenant-occupied houses and apartments for the city of Melbourne from the Local Government Areas editions of the Australian Census of Population and Housing for the years 1954, 1961, 1966, 1971 and 1976. The city of Melbourne was already to a great extent urbanized by 1954, in contrast to the region covered by the Local Government Area of Melbourne. Therefore, our estimates should not be influenced by changes in the urban/rural mix. Like Stapledon (2007), we then interpolated the census years using the national CPI rent component series from ABS.

Table 1.O.2. Final house price index for Melbourne

PERIOD	SOURCE	DESCRIPTION
1880-1970	Stapledon (2012)	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Newspaper ads; *Method*: Median asking prices until 1943 and median sales prices after 1950.
1971-1985	Abelson and Chung (2005)	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Transaction data from Land Title Offices, Productivity Commission and Valuer-General Offices; *Method*: Median prices.
1986-2003	ABS	*Type(s) of dwellings*: New and existing detached houses; *Type of data*: Transaction data from real estate organizations and government agencies; *Method*: Stratification index, where the transactions are stratified by geographical area and physical characteristics of the dwelling.
2004-2018	ABS	*Type(s) of dwellings*: New and existing detached and attached dwellings; *Type of data*: Data obtained from state and territory land title offices or Valuer-General offices, and real estate agents' data provided by *CoreLogic*; *Method*: Stratification index, where the transactions are stratified by dwelling type, long-term median price and a Socio-economic Index for Areas score.

Since 1972, ABS provides a decomposition of the national CPI rent component for eight capital cities, including Melbourne, on a quarterly frequency. These indices are built using the same methodology as for the national series. Rental prices are obtained from real estate agents and territory housing authorities under a matched sample approach, i.e. rents are collected for the same sample of tenant-occupied dwellings every quarter. The samples are stratified according to location, dwelling type, and size of dwelling based on the most recent Census of Population and Housing (Australian Bureau of Statistics (2018)).

Rental Yield Series. For 2018, CoreLogic (2018) reports a gross residential rent-price ratio of 2.8%, which results from a price and rent estimate for the average house in Melbourne. Fox and Tulip (2014) estimate that running costs and depreciation costs amounted to 2.2% of house prices in 2014. We update their estimate to 2018 using price and rent inflation in Melbourne and estimate that in 2018 the costs amount to 1.87% of house prices. Thus, we estimate the net rent-price ratio to be 0.93% in 2018. Applying the rent-price approach to this benchmark gives us the unadjusted long-run net rent-price ratio series depicted as orange circles in Figure 1.O.3. We make some adjustments to these series to correct for possible mismeasurement of rental growth when the wartime price controls were lifted in 1949/50

Table 1.O.3. Final rent index for Melbourne

PERIOD	SOURCE	DESCRIPTION
1901-1954	Stapledon (2007)	*Type(s) of dwellings*: All kinds of tenant and owner-occupied residential dwellings; *Type of data*: Census data; *Method*: Weighted-average gross rents.
1955-1972	Own compilation	*Type(s) of dwellings*: Tenant-occupied residential houses and apartments; *Type of data*: Census data; *Method*: Average weekly gross rent.
1973-2018	ABS	*Type(s) of dwellings*: All kinds of rented residential dwellings; *Type of data*: Rent data are collected from real estate agents and state and territory housing authorities; *Method*: Matched sample approach.

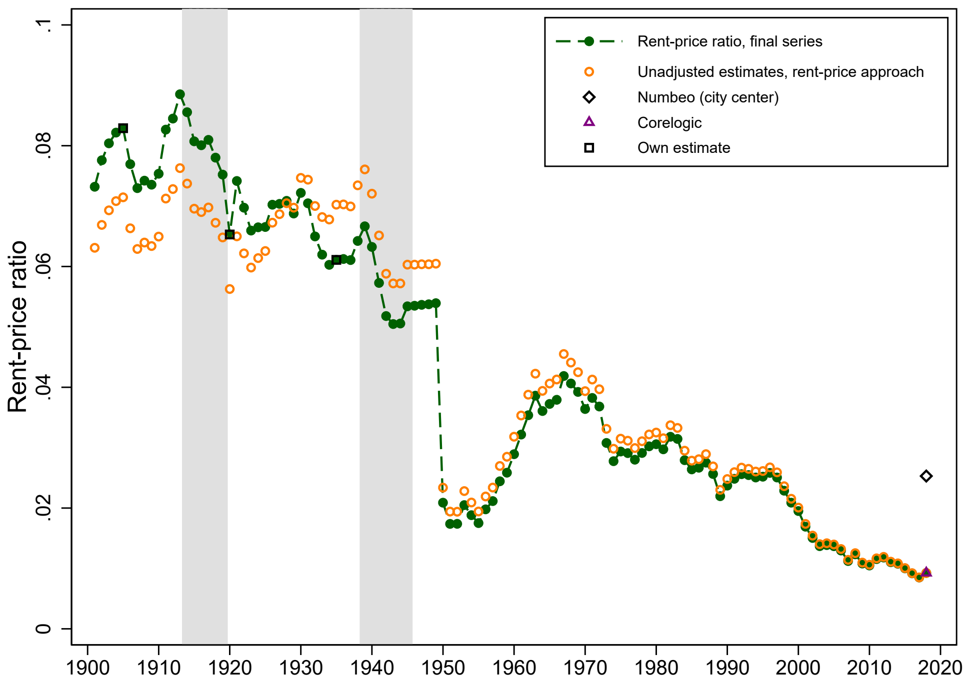

Figure 1.O.3. Melbourne: plausibility of rental yields

(see below for details). This gives us the adjusted final rent-price ratio series—the green-circled line in Figure 1.O.3.

We collected an additional rent-price ratio estimate from *Numbeo.com* for 2018, which is also shown in Figure 1.O.3. *Numbeo.com* reports a gross rent-price ratio of 4.27% for 2018. If we apply the same cost estimate described above, we get to a net estimate of 2.3%, which is higher than the CoreLogic (2018) estimate. Since the *CoreLogic* estimate is derived using a hedonic approach, we decided to choose it over the estimate from *Numbeo.com*, which is a simple average. Furthermore, the *CoreLogic* estimates are constructed using actual price and rent data from land titles and notaries, while the *Numbeo.com* estimates are made using the price and rent estimates given by the website users.

As is clearly visible from Figure 1.O.3, the long-run rent-price ratio shows a structural break in 1949/1950 caused by a surge in house prices after the lifting of wartime price controls in 1949 (price controls for houses and land were introduced in 1942). While it is clear that the end of price controls increased house prices, it is harder to say what effects it had on the relationship between prices and rents. Therefore, we decided to use additional historical benchmarks to adjust our series. Unlike in the case of Sydney, we could not find historical benchmarks for Melbourne. Therefore, we created our own benchmarks using newspaper ads containing asking prices and rents for the exact same residential properties in the city center of Melbourne, i.e. we did not include observations from the suburbs of Melbourne. We arrived at the following estimates of gross rental yields: 11.47% in 1905, 9.77% in 1920 and 8.7% in 1935. We then use the estimates of maintenance costs and depreciation, reported in Table A.22 in Stapledon (2007), to which we add insurance and commissions and deduct property taxes, reported by the *Australian Bureau of Statistics* for census years, which can also be found in Stapledon (2007). Since we only get cost estimates for the years 1900, 1910, 1920, 1932 and 1938, we linearly interpolate the costs for our benchmark years. As a result, we estimate that net yields are 8.29% in 1905, 6.53% in 1920 and 6.11% in 1935. The estimates are shown in the black boxes in Figure 1.O.3.

1.O.1.2 Sydney

House Price Series. Stapledon (2012) builds a long-run house price index for Sydney for the period between 1880 and 2011. His index is based on real estate ads from the newspaper *Sydney Morning Herald* until 1970. For the sub-period 1880–1943, the index is computed from the median asking price for all types of residential buildings, indiscriminate of their characteristics; for 1943–1949, Stapledon (2012) estimates a fixed price;[59] for 1950–1970, he uses the median sales price, which was also reported in the newspaper *Sydney Morning Herald* for this period. For the post-1970 period, Stapledon (2012) uses both Abelson and Chung (2005) as well as Australian Bureau of Statistics (2020), which we explain in more detail below. Stapledon (2012) also discusses other existing historical price series for Syd-

59. A 1943 law fixed nominal house prices in Australia to 1942 levels during this period. The house price freeze ended in 1949, which explains the strong jump in the series between 1949 and 1950.

ney, from Abelson (1985) and Neutze (1972) for the pre-1970 period, and shows that they are strongly correlated with his own series.[60]

Abelson and Chung (2005) build a median house price index for Sydney for the period between 1970 and 2003. For this series they rely on: (i) a 1991 study by *Applied Economics and Travers Morgan*, which draws on sales price data from the *Land Title Offices*, for the period between 1970 and 1979, and (ii) on sales price data from the Department of Housing, i.e. the *North South Wales Valuer-General Office*, for the period between 1980 and 2003.

The *Australian Bureau of Statistics* (ABS) published a quarterly index for Sydney for the period between 1986 and 2005 for i) established detached residential dwellings and ii) *project homes*, i.e. dwellings available for construction on a client's block, excluding land. The indices are calculated using a stratification method, where the transaction prices are stratified by geographical area and physical characteristics of the dwelling (Australian Bureau of Statistics, 1993).

Since 2004, ABS also publishes quarterly indices for Sydney for i) established detached dwellings and ii) attached homes. They additionally publish a third index, which is an aggregation of the first two, which we use to construct our final Sydney house price index. The indices are calculated using a stratification method. Locational, structural and neighborhood characteristics are used to mix-adjust the index, i.e. to control for compositional change in the sample of houses. Each quarter, the strata are re-valued by applying a price relative (i.e. the current period median price of the stratum compared to the previous period median price of the same stratum) to the value of the dwelling stock for that stratum to produce a current period stratum value. The series are constructed as Laspeyres-type indices. Sales price data are taken from the State Valuer-General Offices and are supplemented by data on property loan applications from major mortgage lenders (Australian Bureau of Statistics, 2018).

Table 1.O.4 summarizes the main components of our final house price index. From 1880 to 1970 we rely on the index by Stapledon (2012), because it is the only long-run index and, as mentioned above, correlates very strongly with the other existing indices for the overlapping periods. We then splice the index from Stapledon (2012) with the one from Abelson and Chung (2005) for the period between 1970 and 1986. Abelson and Chung (2005) discuss all existing indices for this period and their choice of final index is based on the representativeness of the underlying data. From 1986 onward, we use the indices produced by the Australian Bureau of Statistics, because these are the only available indices which adjust for quality and compositional changes by applying a stratification index methodology. This is the only period where our series differs from the one in Stapledon (2012).

60. For a clear graphical comparison of the available series for Sydney see Figure 20 of the Online Appendix of Knoll, Schularick, and Steger (2017)

Table 1.O.4. Final house price index for Sydney

PERIOD	SOURCE	DESCRIPTION
1880-1970	Stapledon (2012)	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Newspaper ads; *Method*: Median asking prices until 1943 and median sales prices after 1950.
1971-1985	Abelson and Chung (2005)	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Transaction data from Land Title Offices, Productivity Commission and Valuer-General Offices; *Method*: Median prices.
1986-2003	ABS	*Type(s) of dwellings*: New and existing detached houses; *Type of data*: Transaction data from real estate organisations and government agencies; *Method*: Stratification index, where the transactions are stratified by geographical area and physical characteristics of the dwelling.
2004 - 2018	ABS	*Type(s) of dwellings*: New and existing detached and attached dwellings; *Type of data*: Data obtained from state and territory land titles offices or Valuer-General offices, and real estate agents' data provided by *CoreLogic*; *Method*: Stratification index, where the transactions are stratified by dwelling type, long-term median price and a Socio-economic Index for Areas score.

Rent Series. Stapledon (2007) builds a rent index for Sydney between 1901 and 1954 using adjusted rent estimates for census years (1911, 1921, 1933 and 1947). The estimates are the weighted average of gross rents of tenant-occupied dwellings and the imputed rents of owner-occupied dwellings. The imputed rents are calculated using a 20% premium. These estimates are interpolated using the national CPI rent component from ABS. Whenever the average change between the estimated census years is higher or lower than the change in the national rent index, the author adjusts his results proportional to the difference between rent index rate of change and average change between census data points.

To the best of our knowledge there does not exist a rent index for Sydney for the period between 1955 and 1972. To fill this gap, we collected data on average weekly rent for tenant-occupied houses and apartments for the city of Sydney from the Local Government Areas editions of the Australian Census of Population and Housing for the years 1954, 1961, 1966, 1971 and 1976. Since the region covered by the city of Sydney was already fully urbanized by 1954, in contrast to the region covered by the Local Government Area of Sydney, our estimates are not influenced by changes in the urban/rural mix. Like Stapledon (2007), we then interpolated the census years using the national CPI rent component series from ABS.

Since 1972, ABS provides a decomposition of the national CPI rent component for eight capital cities, including Sydney, on a quarterly frequency. These indices are built using the same methodology as for the national series. Rental prices are obtained from real estate agents and territory housing authorities under a matched sample approach, i.e. rents are collected for the same sample of tenant-occupied dwellings every quarter. The samples are stratified according to location, dwelling type and size of dwelling based on the most recent Census of Population and Housing (Australian Bureau of Statistics (2018)).

Table 1.O.5. Final rent index for Sydney

PERIOD	SOURCE	DESCRIPTION
1901 - 1954	Stapledon (2007)	*Type(s) of dwellings*: All kinds of tenant and owner-occupied residential dwellings; *Type of data*: Census data; *Method*: Weighted-average gross rents.
1955 - 1972	Own compilation	*Type(s) of dwellings*: Tenant-occupied residential houses and apartments; *Type of data*: Census data; *Method*: Average weekly gross rent.
1973 - 2018	ABS	*Type(s) of dwellings*: All kinds of rented residential dwellings; *Type of data*: Rent data are collected from real estate agents and state and territory housing authorities; *Method*: Matched sample approach.

Rental Yield Series. For 2018, CoreLogic (2018) reports a gross residential rent-price ratio of 3.1%, which results from a price and rent estimate for the average house in Sydney. Fox and Tulip (2014) estimate that running costs and depreciation costs amounted to 2.2% of house prices in 2014. We update their estimate to 2018 using price and rent inflation in Sydney and estimate that in 2018 the costs amount to 1.95% of house prices. Thus, we estimate the net rent-price ratio to be 1.15% in 2018. Applying the rent-price approach to this benchmark gives us the unadjusted long-run net rent-price ratio series depicted as orange circles in Figure 1.O.4. We make some adjustments to these series to correct for possible mismeasurement of rental growth when the wartime price controls were lifted in 1949/50 (see below for details). This gives us the adjusted final rent-price ratio series—the green-circled line in Figure 1.O.4.

We collected an additional rent-price ratio estimate from *Numbeo.com* for 2018, which is also shown in Figure 1.O.4. *Numbeo.com* reports a gross rent-price ratio of 4.27% for 2018. If we apply the same cost estimate described above, we get to a net estimate of 2.3%, which is higher than the CoreLogic (2018) estimate. Since the *CoreLogic* estimate is derived using a hedonic approach, we decided to choose it over the estimate from *Numbeo.com*, which is a simple average. Furthermore, the

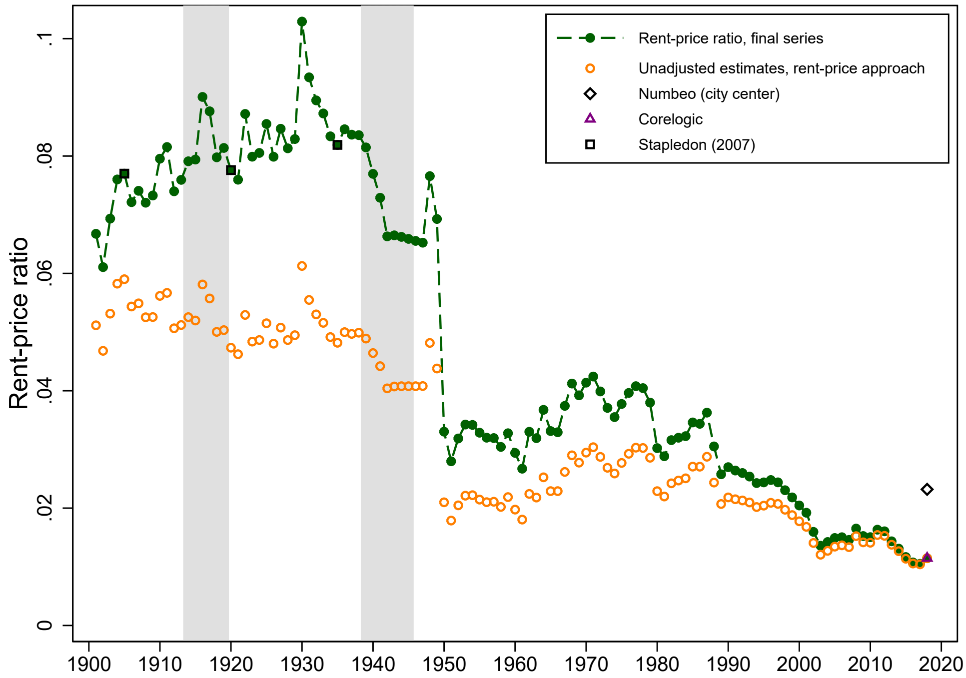

Figure 1.O.4. Sydney: plausibility of rental yields

CoreLogic estimates are constructed using actual price and rent data from land titles and notaries, while the *Numbeo.com* estimates are made using the price and rent estimates given by the website users.

As is clearly visible from Figure 1.O.4, the long-run rent-price ratio shows a structural break in 1949/1950 caused by a surge in house prices after the lifting of wartime price controls in 1949 (price controls for houses and land were introduced in 1942). While it is clear that the end of price controls increased house prices, it is harder to say what effects it had on the relationship between prices and rents. Therefore, we decided to use additional historical benchmarks from Stapledon (2007) to adjust our series. The estimates are shown in the black boxes in Figure 1.O.4. The gross rent-price ratio estimates for 1905, 1920 and 1935 were built from newspaper ads. We built net rent-price ratios using the estimates on running costs and depreciation combined with tax data also reported in Stapledon (2007). We estimate that costs and taxes represented around 27.8% of prices in 1900, 33.2% in 1920 and 30.4% in 1938. We assume linear changes in costs relative to house prices over time to estimate the net rent-price ratios for the benchmark years.

1.O.2 Canada

According to the Canadian census the five largest cities in Canada in 1901 were in descending order: Montreal, Toronto, Vancouver, Quebec, Ottawa. All of them encompassed more than one percent of the country population in 1901.[61] It is important to note that the estimate for Vancouver is taken as the sum of Burrard and Vancouver city from the Canadian population census from 1901. Burrard officially became part of the city of Vancouver in 1904.

Together, Toronto and Vancouver represented less than 10% of Canada's population in 1901. Unfortunately, we are not aware of historical house price and rent series for other cities in the country. As such, we limit ourselves to these two cities.

Generally speaking there is very limited work on historical housing series for Canadian cities. As shown below, most of the price and rent indices for Toronto and Vancouver are composed of new indices.

For the last few decades, particularly since the 1980s, both Statistics Canada as well as the Canada Mortgage and Housing Corporation have started publishing housing data for different Canadian cities. More recently, the Canadian Real Estate Board started publishing a high-quality house price index at the regional level, which we describe in more detail below.

1.O.2.1 Toronto

House Price Series. Firestone (1951) uses data from the value of real estate transfers in Toronto based on tax records and registry entries to construct a series of total value of residential real estate in Toronto for the period between 1921 and 1949.

Morrison (1978) uses data on single-family and two-family houses to build a repeat-sales index for the city center of Toronto for the period between 1951 and 1973.[62]

The University of British Columbia (UBC) published a house price index for Toronto, which covers the period between 1975 and 2012. The index is based on prices for existing bungalows and two-story executive detached houses in Toronto (Urban Economics and Real Estate, 2013). The index is built by using a population weighted average of the price change in each neighborhood for which data are available. Subsequently, the index is weighted on changes in the price level of different housing types, i.e. detached bungalows and executive detached houses, according to their share in total units sold. Data are drawn from the house price survey of the real estate company *Royal LePage*.

61. City-level population data are taken from the Canadian Population Census of 1901 (*Fourth census of Canada, 1901,* 1901) and country-level population data from Jordà, Schularick, and Taylor (2017).

62. For more details please refer to Revilla (2021)

The *Toronto Real Estate Board* has published historical data from average prices that were listed in the Multiple Listings Service (MLS) since 1975; however, these estimates also include commercial real estate (Board, 2021).

Statistics Canada publishes a house price index based on the price of new dwellings since 1981. The price data on single-family homes, semi-detached homes and townhomes (row or garden homes) come from a survey conducted by *Statistics Canada* on real estate contractors, which covers at least 15% of the total building permit value in Toronto in a given year. Since the survey also includes questions on the characteristics of the properties, *Statistics Canada* is able to construct a matched-model index, in which only similar properties are compared over time (Canada, 2021b).

Since a continuous quality-adjusted long-run index was missing for Toronto, Amaral et al. (2021) built a hedonic house price index for the period between 1900 and 1990 for a companion project on long-run regional housing prices in Canada.[63] To construct the series the authors collected asking prices on residential dwellings from the real estate advertisement section of the local newspaper *Toronto Star*. On average, 200 observations per year are used to estimate a house price index based on a hedonic time-dummy adjacent period approach. More precisely, the authors regress the log asking price on time dummies and on the following house characteristics: type of property (house, detached house or apartment), size (number of rooms), location (city center or suburbs), whether the dwelling is new or not and other features (whether it has a garage, swimming pool, air conditioning).[64]

Revilla (2021) compares the long-run index in Amaral et al. (2021) with the existing indices for Toronto. When comparing to the index by Firestone (1951) the long-run index shows less volatility and price appreciation between 1921 and 1949, which we would expect since the series by Firestone do not adjust for quality changes in the sample. With respect to the index by Morrison (1978) and the more recent indices from MLS, UBC and *Statistics Canada* the long-run index shows the exact same trends and a very high level of correlation across time.

Table 1.O.6 summarizes the components of our final house price index. We decided to use series from Amaral et al. (2021) for the period between 1900 and 1990 mainly for two reasons. First, because it is the only continuous long-run house price index for Toronto and starts earlier than all existing series. Second, because it correlates very strongly with existing quality-adjusted series for the last decades and, therefore, we preferred to keep the same series over time. For the period after 1990, we opted for the index from Statistics Canada, since it is the only quality-adjusted index which covers the complete period until 2018.

63. For more details about this project as well as Canadian housing series please refer to Amaral et al. (2021).

64. For more details about the construction of the index please refer to Revilla (2021).

Table 1.O.6. Final house price index for Toronto

PERIOD	SOURCE	DESCRIPTION
1900-1990	Amaral et al. (2021)	*Type(s) of dwellings*: Houses, detached houses and apartments; *Type of data*: Asking prices from the *Toronto Star*; *Method*: Hedonic time-dummy adjacent period index.
1991-2018	Canada (2021b)	*Type(s) of dwellings*: New owner-occupied dwellings; *Type of data*: Transaction prices from housing survey ; *Method*: Matched-model price index.

Rent Series. Amaral et al. (2021) also built a rent price index using real estate ads from the *Toronto Star*. Due to the lack of ads in the first two decades of the 20th century, the rent index starts in 1921. The same methodology as in the house price index is used, i.e. the index is built using a hedonic time-dummy adjacent period method, which controls for the same set of characteristics as listed above in the description of the long-run house price index. Since the number of observations is very low for the period between 1943 and 1950, we considered the index not to be of sufficient quality to be published. As a result the final rent index has a gap between 1943 and 1950.

Statistics Canada publishes a rented accommodation index for the census metropolitan area of Toronto since 1971 as part of the Toronto consumer price index (CPI). The index is based on data from the Labour Force Survey (LFS), which is conducted on a monthly basis for a rotating representative sample, such that the rent of the same dwelling is always recorded for six successive months (Claveau, Lothian, and Gauthier, 2009). This allows *Statistics Canada* to build the rental index by matching the rents for the same dwellings across time, thereby constructing a quality-adjusted rental index. The sampling method used by *Statistics Canada* also implies that only one sixth of the dwellings sampled each period are new in the sample. This means that, by construction, the index mostly tracks the price evolution of existing rental contracts.

Statistics Canada also publishes the average rental value for dwellings of different sizes for the Toronto metropolitan area since 1987. The data come from a yearly survey conducted by the *Canada Mortgage and Housing Corporation* (CMHC) in different Canadian cities including Toronto. The average rental values are built each year for apartments of different sizes in buildings of different sizes. However, the only series which starts already in 1987 is the series for the rental value of apartments in buildings with six or more apartments.[65] We build an average rent index by

65. Canada, 2021c.

taking a yearly unweighted average of the rental values for apartments of different sizes in buildings with six or more apartments.[66]

Revilla (2021) builds a decadal rent index for Toronto using census data on average rent paid for the city of Toronto for the period between 1921 and 1981. The author shows that the long-run rental index in Amaral et al. (2021) and the index built using census data follow the same trend between 1920 and 1980.

Revilla (2021) shows that for the period between 1971 and 1990 the indices from Amaral et al. (2021) and from *Statistics Canada* show significantly different trends, with the series in Amaral et al. (2021) growing substantially more in this period. One major difference between the two indices relates to the fact that Amaral et al. (2021) use only data on new rental contracts, which often included rents on newly constructed buildings, while *Statistics Canada* mostly use data on existing rental contracts. This is especially important, since new buildings were not subject to rent controls, which were introduced in 1975 in the province of Ontario.[67] As a result, by construction, the index in Amaral et al. (2021) reflects to a much larger extent rental price evolution in the rental sector not exposed to the rental control laws. This explains the fact that the index grows more in this period than the index by *Statistics Canada*.

Comparing the CPI rent component index from *Statistics Canada* with the CMHC index for the period between 1990 and 2018 produces very similar results. While the CMHC index grows by a factor of approximately 2 in this period, the CPI rent component grows only by 50%. We know that by construction the CMHC index also takes into account rental contracts in newly constructed dwellings, which might explain these differences.

Table 1.O.7 summarizes the components of our final rent index. From 1921 to 1990 we use the index from Amaral et al. (2021). Since our long-run house price index only reflects the price evolution of newly constructed dwellings in Toronto after 1990, we decided to use the CMHC rent index for that period. Using the rent component of the CPI index would create a very large wedge in terms of the types of dwellings being covered by the rent and price series, since the price series only uses data on newly constructed dwellings for the period after 1990.

Rental Yield Series. Our main benchmark for Toronto is taken from *MSCI*, as described in the main paper. This benchmark is slightly above the benchmark we collected for 2018 from *Numbeo.com*. According to *Numbeo.com* the gross rental yield in the city center of Toronto was 4.5% in 2018, adjusting for one-third costs we estimate a rental yield of 3% for 2018. Applying the rent-price approach to our

66. To distinguish this index from the other one published by Statistics Canada, we will refer to this one as the CMHC index.

67. See Revilla (2021) for a detailed description of rent control laws in Canada throughout the twentieth century.

Table 1.O.7. Final rent index for Toronto

PERIOD	SOURCE	DESCRIPTION
1921-1990	Amaral et al. (2021)	*Type(s) of dwellings*: Houses, detached houses and apartments; *Type of data*: Asking rents from the newspaper *Toronto Star*; *Method*: Hedonic time-dummy adjacent period index.
1991-2018	Canada (2021c)	*Type(s) of dwellings*: Apartments in buildings with six or more apartments; *Type of data*: Rents from the Canada Mortgage and Housing Corporation Survey; *Method*: Average rental value.

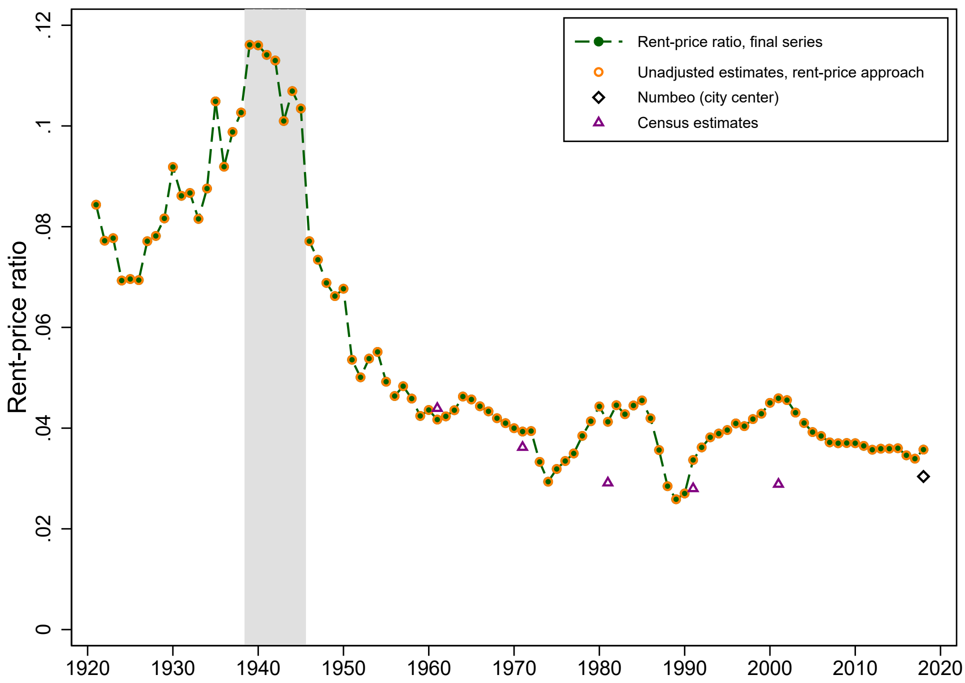

Figure 1.O.5. Toronto: plausibility of rental yields

main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.5.

Using census household-level data based on a representative sample of the metropolitan area of Toronto we were able to build average gross yields for the years 1971, 1981, 1991 and 2001 using a matching approach.[68] We built average rental yields, by matching the average rent of renter-occupied dwellings with the average

68. The so-called public use microdata file (PUMF) can be accessed by researchers via *Statistics Canada*.

value of owner-occupied dwellings of the same type and with the same number of rooms within urban areas of the metropolitan area of Toronto.[69] We then aggregate the average gross yields using the number of observations of the respective dwelling type and number of rooms combinations as weights. For the year 1961 the household-level data are not available. Therefore, we build a benchmark for 1961, using the median value of owner-occupied single-detached non-farm houses for the city of Toronto and the average rent paid for renter-occupied non-farm dwellings for the city of Toronto from the national housing census in 1961 (*1961 Census of Canada : Housing Vol. II,* 1961).[70] We then adjust the gross yield estimates for one-third costs and get the net yield estimates, which are depicted in Figure 1.O.5. While the census estimates for 1981 and 2001 lie slightly below our unadjusted rental yield series, in general the census estimates match our series quite accurately. As a result we do not adjust our rental yield series.

As is visible from Figure 1.O.5 there is a downward jump in our rental yield series from 1945 to 1946. As we mentioned above, our final rent index has a gap between 1943 and 1950. To build a continuous rental yield series we had to linearly interpolate the rent index for this period. As a result the yearly changes in rental yield series are mostly a product of the changes in the price series for this period. However, to the best of our knowledge, there do not exist rental yield benchmarks for the pre-1950 period which would allow us to better understand the actual rental yields in Toronto for this period.

1.O.2.2 Vancouver

House Price Series. The University of British Columbia (UBC) published a house price index for Vancouver, which covers the period between 1975 and 2012. The index is built using the exact same data sources and methods as the one for Toronto. For more details about the series please refer to the Toronto data appendix.

Amaral et al. (2021) built a hedonic house price index for the city of Vancouver for the period between 1950 and 1984 using asking prices from newspaper real estate ads from the *The Vancouver Sun*. On average, 250 observations per year are used to estimate a house price index based on a hedonic time-dummy adjacent period approach. More precisely, the authors regress the log asking price on time dummies and on the following house characteristics: type of property (house, bungalow or duplex), size (number of rooms, bathrooms and kitchen), location (neighborhood) and other features (whether it has a garage, garden or a basement).[71]

69. The types of dwellings were the following: single-family houses, semi-detached, rowhouse, duplex, apartment and mobile.

70. Unfortunately, the censuses prior to 1961 do not contain information on the value of dwellings.

71. We have data on the following 22 neighborhoods in the city of Vancouver: Arbutus Ridge, Downtown, Dunbar-Southlands, Fairview, Grandview-Woodland, Hastings-Sunrise, Kensington-Cedar Cottage, Kerrisdale, Killarney, Kitsilano, Marpole, Mount Pleasant, Oakridge, Renfrew-Collingwood, Riley

Statistics Canada publishes a house price index based on the price of new dwellings since 1981 for Vancouver. The methods and data sources are exactly the same as the ones for Toronto. For more details about the series please refer to the Toronto data appendix.

The *Canadian Real Estate Association* together with the regional real estate associations publishes the MLS HPI index since 2005 for different Canadian metropolitan areas. The index is built based on transaction data from the multiple listing service's database (MLS), which contains practically the whole universe of real estate transactions in Canada. The index is built separately for different types of residential dwellings using a hedonic approach.[72] The hedonic regressions are built on an extensive set of geographical, size of property and local amenities controls.[73] The hedonic regressions for the different residential dwelling types are used to impute the price of a dwelling whose attributes are typical of the dwellings traded in the area where it is located. These imputed prices are then aggregated to a composite price of the metropolitan area using the number of sales as weights. A Fisher chained index methodology is then used to link the imputed prices for the different time periods.

Table 1.O.8 summarizes the components of our final house price index. From 1950 to 1984 we use the hedonic index by Amaral et al. (2021). From 1985 to 2004 we use the price index from *Statistics Canada* on newly built dwellings. After 2005, we rely on the MLS hedonic index. The reason for this is that the index from *Statistics Canada* rises substantially less than the one from MLS after 2005. Since the data and methodologies used to build the MLS index are considerably better, we think that the MLS index is more reliable.

Rent Series. Amaral et al. (2021) built a rent price index for Vancouver for the period between 1950 and 1984 based primarily on real estate rental ads from the *Vancouver Sun*.[74] On average, 250 observations per year are used to estimate a rent price index based on a hedonic time-dummy adjacent period approach. More precisely, the authors regress the log asking yearly rent on time dummies and on the following house characteristics: type of property (single-family house, bungalow, apartment or duplex), size (number of rooms, bathrooms and kitchen), location

Park, Shaughnessy, South Cambie, Strathcona, Sunset, Victoria-Fraserview, West End and West Point Grey.

72. The different types of dwellings are the following: single-family houses, one-story house, two-story houses, townhouses and apartments.

73. For an exact description of the data and methods used to build the MLS HPI index please refer to Association (2021b).

74. For the year 1981, the authors collected additional observations from the newspaper *Vancouver Heights*.

Table 1.O.8. Final house price index for Vancouver

PERIOD	SOURCE	DESCRIPTION
1950-1984	Amaral et al. (2021)	*Type(s) of dwellings*: House, bungalow or duplex; *Type of data*: Asking prices from the *Vancouver Sun*; *Method*: Hedonic time-dummy adjacent period index.
1985-2004	Canada (2021b)	*Type(s) of dwellings*: New owner-occupied dwellings; *Type of data*: Transaction prices from housing survey; *Method*: Matched-model price index.
2005-2018	Association (2021a)	*Type(s) of dwellings*:Single-family house, townhouses and apartments; *Type of data*: Transaction prices from the MLS database; *Method*: Chained Fisher index based on imputed hedonic approach.

(neighborhood) and other features (whether it has a garage, garden or a basement).[75]

Statistics Canada publishes a rented accommodation index for the census metropolitan area of Vancouver since 1971 as part of the Vancouver consumer price index (CPI). Just like in the case of Toronto, the index is based on data from the Labour Force Survey (LFS). For more details about the series please refer to the Toronto data appendix.

Statistics Canada also publishes the average rental value for dwellings of different sizes for the Vancouver metropolitan area since 1987. As for Toronto, the data come from a yearly survey conducted by the *Canada Mortgage and Housing Corporation* (CMHC). We build an average rent index by taking a yearly unweighted average of the rental values for apartments of different sizes in buildings with six or more apartments.[76]

Table 1.O.9 summarizes the components of our final rent index. From 1950 to 1984 we rely on the hedonic rent index from Amaral et al. (2021), since this index is based on the same method of our house price index for Vancouver for the same period. Between 1984 and 1987 we use the rent component of the CPI by *Statistics Canada*. From 1988 onward we rely on the index on the CMHC average rent index for Vancouver. As in the case of Toronto, we think that this index better captures the

75. We have data on the following 22 neighborhoods in the city of Vancouver: Arbutus Ridge, Downtown, Dunbar-Southlands, Fairview, Grandview-Woodland, Hastings-Sunrise, Kensington-Cedar Cottage, Kerrisdale, Killarney, Kitsilano, Marpole, Mount Pleasant, Oakridge, Renfrew-Collingwood, Riley Park, Shaughnessy, South Cambie, Strathcona, Sunset, Victoria-Fraserview, West End and West Point Grey.

76. To distinguish this index from the other one published by *Statistics Canada*, we will refer to this one as the CMHC index.

rent price dynamics in the overall market, including newly constructed buildings. As a result it matches our final house price index better.

Table 1.O.9. Final rent index for Vancouver

PERIOD	SOURCE	DESCRIPTION
1950-1984	Amaral et al. (2021)	*Type(s) of dwellings*: Single-family house, bungalow, apartment and duplex; *Type of data*: Asking rents from the *Vancouver Sun* and the *Vancouver Heights*; *Method*: Hedonic time-dummy adjacent period index.
1985-1987	Canada (2021a)	*Type(s) of dwellings*: Renter-occupied dwellings; *Type of data*: Rents from the Labour Force Survey by Statistics Canada; *Method*: Match-model approach.
1988-2018	Canada (2021c)	*Type(s) of dwellings*: Apartments in buildings with six or more apartments; *Type of data*: Rents from the Canada Mortgage and Housing Corporation Survey; *Method*: Average rental value.

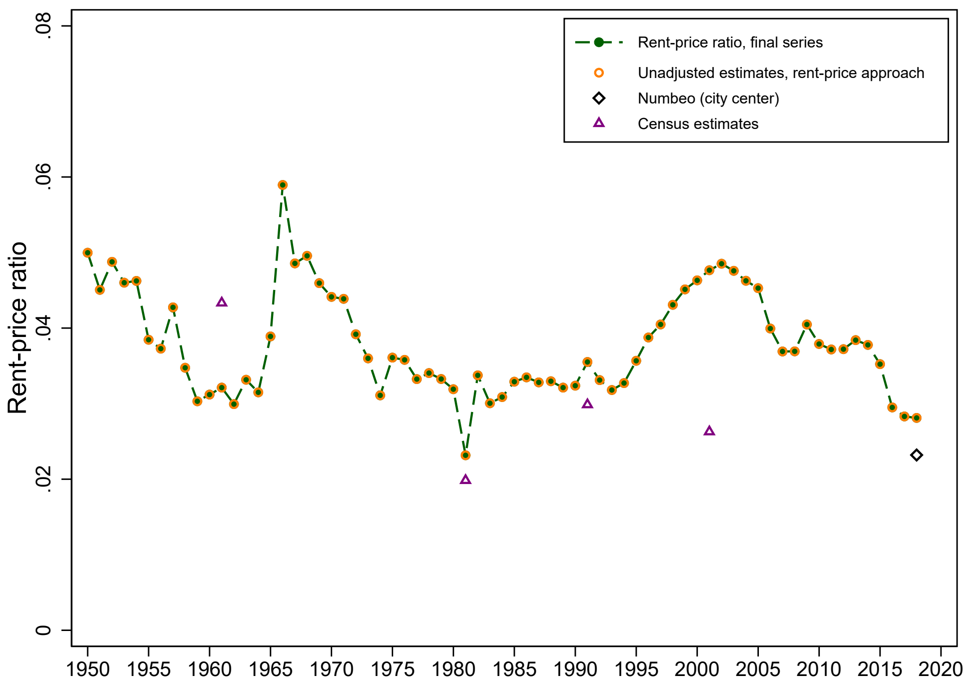

Figure 1.O.6. Vancouver: plausibility of rental yields

Rental Yield Series. Our main benchmark for Vancouver is taken from *MSCI*, as described in the main paper. This benchmark is slightly above the benchmark we collected for 2018 from *Numbeo.com*. According to *Numbeo.com* the gross rental yield in the city center of Vancouver was 3.48% in 2018, adjusting for one-third costs we estimate a net rental yield of 2.3% for 2018. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.6.

We use the same approach as in the case of Toronto to build historical rental yield benchmarks out of census data. Unfortunately, the household-level data from 1971 census does not contain data for Vancouver. As such, we were only able to construct benchmarks for the years 1981, 1991 and 2001. We use the exact method as the one described in the Toronto data appendix. Additionally, we also build a benchmark for 1961, using the median value of owner-occupied single-detached non-farm houses for the city of Vancouver and the average rent paid for renter-occupied non-farm dwellings for the city of Vancouver from the national housing census in 1961 (*1961 Census of Canada : Housing Vol. II,* 1961). As such, the benchmark for 1961 is only a rough approximation to actual rental yield in Vancouver at the time. We then adjust the gross yield estimates for one-third costs and get the net yield estimates, which are depicted in Figure 1.O.6. While the census estimates for 1961 and 2001 lie slightly above and below our unadjusted rental yield series respectively, in general the census estimates match our series quite accurately. As a result we do not adjust our rental yield series.

1.O.3 Denmark

Copenhagen has been Denmark's largest city by far, with 462,000 inhabitants or eighteen percent of the total population in 1900 (followed by Aarhus, Odense, Aalborg and Vilborg with 51,000 or less). It is also the only city for which there are existing house price series and some available data on rent prices before 1970, where we had to construct new rent price series ever since.

1.O.3.1 Copenhagen

House Price Series. Prior to 1938, there is no existing house price index in Copenhagen (even the national-level data are based on farm prices). Since 1938, we draw on a a stratified Fisher index provided by Abildgren (2018) for the city of Copenhagen, based on transaction data from single-family houses by number of rooms. The strata are built using the housing stock for every five years. The source are official statistical publications from *Statistics Denmark*. From 1992 onward we use an index for single-family houses from Statistics Denmark (2021). The index is based on high-quality transaction-level data from the Ministry of Taxation which are collected weekly through an electronic land registration system. It uses the SPAR method and covers Greater Copenhagen. We use yearly averages of the quarterly index. The components of our final house price index are summarized in Table 1.O.10.

Table 1.O.10. Final house price index for Copenhagen

PERIOD	SOURCE	DESCRIPTION
1938-1992	Abildgren (2018)	*Type(s) of dwellings*: Single-family houses; *Type of data*: Transaction data; *Method*: Stratification index
1992-2018	Statistics Denmark and Tax Authorities	*Type(s) of dwellings*: Single-family houses; *Type of data*: Transaction level data from taxation records; *Method*: SPAR method.

Rent Series. Data for the rent series in Copenhagen come from a number of different sources. For the time period between 1885 and 1970, we draw on various years of the city yearbooks published by the *Copenhagen Statistical Office*. The yearbooks report every five years the annual rent for all rented dwellings in Copenhagen by number of rooms. Every five years we take a weighted average of the yearly average rent for dwellings with different numbers of rooms. The years in between are linearly interpolated.

From 1970 onward we constructed a new rent series. It is composed of different parts. From 1970 to 1990 we build a hedonic rent index using rental ads from a local newspaper, *Berlingske*, which publishes a small daily and a longer weekly section on real estate. We located and scanned the relevant pages from microfilm and extracted all ads containing at least information on rent, size and location. This produces a sample of 957 ads with complete information. The rental market sections mainly contained two segments, one on renting single-family houses also located in the Copenhagen region, one on rental apartments, predominantly in the city of Copenhagen. Our ads cover both market segments. We use a hedonic regression of the log rent levels on year dummies, controlling for a dummy for the market segments, city district dummies, a dummy for furnished units and housing size. We harmonized housing size by converting square meters into 0.023 rooms, based on our within-sample estimates. The explained variance is 0.852.

From 1990 to 2000 we use a weighted average of the house price indices published by the newspaper *The Economist*. The *Economist Intelligence Unit* publishes yearly data on living costs in global cities, containing information on rent levels by different room and quality bins. We average the data for all bins containing full information over time.

From 2000 onward, we accessed the archived real estate websites *boligportal*, *akutbolig* and *bolig-siden* and collected 728 rental ads on apartments for Greater Copenhagen containing full information on rents, size and location. We use a hedonic regression of the log rent levels on year dummies, including as control variables a dummy for the rental market segments, dummies for the city districts, a dummy for furnished units and housing size. We harmonized housing size by converting square meters into 0.023 rooms, based on our within-sample estimates. The explained variance is 0.721.

Table 1.0.11. Final rent index for Copenhagen

PERIOD	SOURCE	DESCRIPTION
1885-1970	City Yearbooks of Copenhagen (several issues)	*Type(s) of dwellings*: Apartments; *Type of data*: Municipal survey data; *Method*: Stratification index (interpolated).
1970-1990	Own series	*Type(s) of dwellings*: Single-family houses and apartments; *Type of data*: Newspaper ads from *Berlingske*; *Method*: Hedonic index.
1990-2000	The Economist	*Type(s) of dwellings*: Apartments with two to four bedrooms; *Type of data*: Estimates of the *Economist Intelligence Unit*; *Method*: Average over quality bins.
2000-2018	Own series	*Type(s) of dwellings*: Single-family houses and apartments; *Type of data*: Ads from real estate website *boligportal*; *Method*: Hedonic index.

Rental Yield Series. Our main benchmark for Copenhagen is taken from *MSCI*, as described in the main paper. Applying the rent-price approach to this benchmark

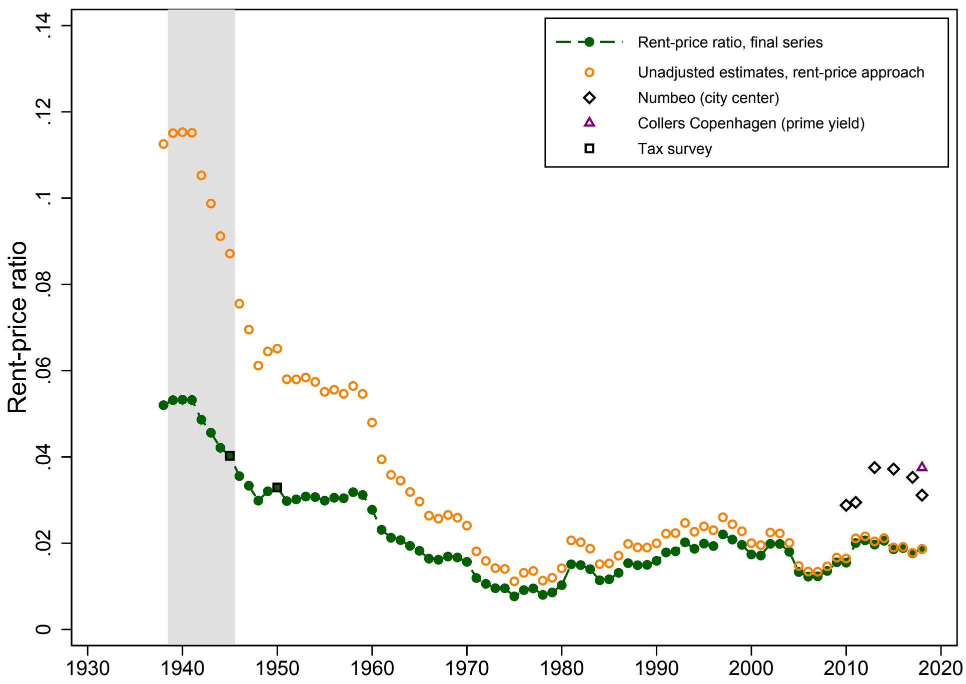

Figure 1.O.7. Copenhagen: plausibility of rental yields

results in the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.7.

We collected two additional benchmarks for 2018. First, we use the gross rental yield for the city-center of Copenhagen from *Numbeo.com*. We adjust this benchmark to capture the net rental yield by subtracting one-third following Jordà et al. (2019). Secondly, we collected a recent benchmark from *Collers Copenhagen*. Both benchmarks are somewhat above but reasonably close to our main benchmark from *MSCI*. We use the benchmark by *Numbeo.com* as our alternative benchmark in the robustness section of the main paper. We also collected additional rental yield benchmarks from *Numbeo.com* between 2010 and 2018. These benchmarks show a very similar pattern as our long-run net rental yield series and the value in 2010 is close to our long-run series.

To collect historical benchmarks, we draw on data from the 1950 publication of Statistics Denmark's *Vurderingen til Grundskyld og Ejendomsskyld*, an assessment of property values and rents for taxation purposes. The rental yields are computed as weighted average of the ratio of imputed rents to property values for residential real estate in Copenhagen, using the number of properties with different housing units as weights. The resulting benchmarks are clearly below our unadjusted series. As we have to rely on interpolation to construct our long-run rent series and the level of rent controls in Denmark were historically high, it could be the case that our long-run rental yield series are biased. Therefore we adjust our series to these benchmarks. The final rental yield series is plotted as the green-circled line in Figure 1.O.7.

1.O.4 Finland

In 1900 the three largest cities in Finland were in descending order: Helsinki, Tammerfors and Abo. All of these cities had more than 1% of the total national population in 1900. Unfortunately, we could only build long-run house and rent indices for Helsinki, since we could not find existing series or primary sources for the other two cities.

1.O.4.1 Helsinki

House Price Series. The long-run house price series for Helsinki covers the period between 1946 and 2018 and is composed of three different series. For the period between 1946 and 1970 we take the average price per square meter of dwellings in existing blocks of apartments in the center of Helsinki from *Statistics Finland*.[77] The transaction data were collected by *Statistics Finland* from different local real estate agencies.[78]

For the period between 1971 and 1988 we use a mix-adjusted hedonic house price index from *Statistics Finland* for the city of Helsinki. The index is based on transaction prices of dwellings in existing blocks of apartments and the data come from the *Finnish Tax Administration*. *Statistics Finland* uses housing stock weights to aggregate the hedonic indices for apartments with different numbers of rooms.[79]

For the period between 1988 and 2018 we use a mix-adjusted hedonic house price index from *Statistics Finland* for the city of Helsinki. The index is based on transaction prices of dwellings in existing terraced houses and existing blocks of apartments gathered by the *Finnish Tax Administration* for asset transfer tax calculation purposes, which are stratified by type of dwelling, number of rooms and location. The housing stocks of each strata are used as weights to build the final index.[80]

Statistics Finland also publishes a house price index of single-family houses for the Greater Helsinki area.[81] The index is a mix-adjusted hedonic index, where single-family houses are stratified by number of rooms and location. A hedonic regression is then applied to estimate the price index for each stratum. The strata are then combined using the housing stock as weights. The data on transaction prices come from the real estate register of the *National Land Survey of Finland* and they are combined with data from the real estate information system of the *Population Register Centre*.[82]

77. Existing blocks of apartments are buildings which were built at least two years before the publication of the series.
78. Statistics Finland, 2020a.
79. Statistics Finland, 2020a.
80. More information can be found in Statistics Finland (2020a).
81. Greater Helsinki includes the cities Helsinki, Espoo, Vantaa and Kauniainen.
82. Statistics Finland, 2020b.

The index on single-family houses correlates very strongly with the index on existing dwellings.[83] Since the latter covers only the city of Helsinki, i.e. it excludes the the other cities in the Greater Helsinki area, we opted to choose it for our final series.

Table 1.O.12 summarizes the components of our final house price index.

Table 1.O.12. Final house price index for Helsinki

PERIOD	SOURCE	DESCRIPTION
1946-1970	Statistics Finland (2020a)	*Type(s) of dwellings*: Dwellings in existing blocks; *Type of data*: Average transaction price per square meter; *Method*: Average.
1970-1988	Statistics Finland (2020a)	*Type(s) of dwellings*: Dwellings in existing blocks; *Type of data*: Transaction prices; *Method*: Mix-adjusted hedonic price index.
1988-2018	Statistics Finland (2020a)	*Type(s) of dwellings*: Existing dwellings; *Type of data*: Transaction prices; *Method*: Mix-adjusted hedonic price index.

Rent Series. Our long-run rent series for Helsinki also covers the period between 1946 and 2018 and is composed of two different series. To build the series we collected average rents of apartments in the city of Helsinki by number of rooms from the Helsinki statistical yearbook.[84] From 1946 to 1974 we build a stratified Fisher index using the stock of apartments by number of rooms as weights. On average, we have the stock of apartments by number of rooms every five years. Since data are missing for the years 1948, 1949, 1951, 1952, 1953, 1955 and 1956 we interpolate the index for those years using the national rent index from Jordà et al. (2019). For the period after 1974 we construct a chained stratification Fisher index using the stock of apartments of the last available data point as weights.[85]

Table 1.O.13 summarizes the components of our final rent index.

Rental Yield Series. Unfortunately, *MSCI* does not provide an estimate for Helsinki. As a result we benchmark our series to the estimate from *Numbeo.com* for 2018 for Helsinki city center. According to *Numbeo.com* the gross rental yield was 3.06%, to which we subtract one-third costs. According to *KTI*, a Finnish property markets analysis firm, the gross yield on residential property in the city center of Helsinki was 3.7%.[86] Applying again one-third costs, we get a net-yield benchmark of 2.4% for 2018, which is very close to the estimate from *Numbeo.com*. Applying

83. Over the period between 1985 and 2018 the two indices have a correlation of 0.98.
84. *Statistical Yearbook of the City of Helsinki,* various years.
85. From 2005 onward data on the stock of apartments are available every year.
86. *The Finnish Property Market, 2019,* 2019.

Table 1.O.13. Final rent index for Helsinki

PERIOD	SOURCE	DESCRIPTION
1946-1975	Own compilation	*Type(s) of dwellings*: Apartments ; *Type of data*: Average rents; *Method*: Fisher stratified index using stocks as weights.
1975-2018	Own compilation	*Type(s) of dwellings*: Apartments ; *Type of data*: Average rents; *Method*: Chained fisher stratified index using stocks as weights.

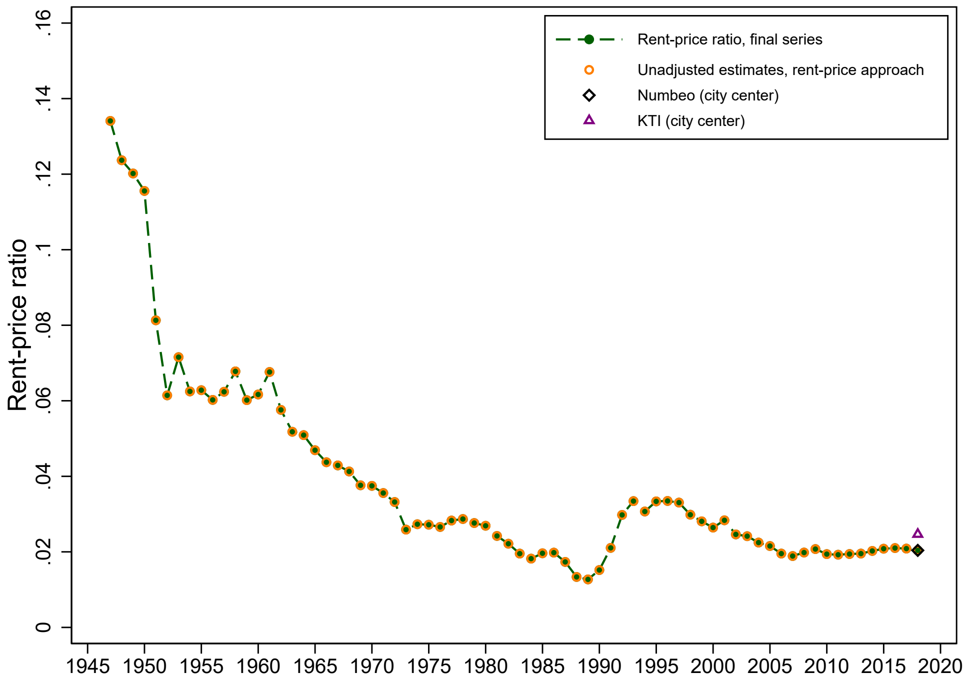

Figure 1.O.8. Helsinki: plausibility of rental yields

the rent-price approach to this benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.8.

Unfortunately, we were not able to find any historical benchmarks for Helsinki. As a result our final adjusted rental yield series — the green-circled line in Figure 1.O.8 - matches the unadjusted series, which features very high values before 1950. The considerable drop around 1950 might be driven by the relaxation of wartime rent controls during this period. We can, however, not exclude that our long-run rental yield series is biased for the earlier period due to the fact that our house price index is based on a simple average and, thus, does not control for sample shifts and quality changes over time. This problem might be especially relevant in the direct aftermath of World War II, when the local housing market was still recovering from the damages of the war. Since our main analysis only starts in 1950, this bias is probably less relevant for our main results.

1.O.5 France

In 1900 the four largest cities in France were in descending order: Paris, Lyon, Marseille and Bordeaux. With the exception of Bordeaux, all of these represented more than 1% of the national population in 1900.[87]

To the best of our knowledge there do not exist continuous long-run series for Marseille and Lyon. As such, we only produced a long-run series for Paris. However, Bonneval and Robert (2010) build a housing return series for Lyon for the period between 1890 and 1968 based on archival data from a local real estate company. Future work will, hopefully, complement this series to builds a representative housing return series of the city of Lyon. The scarcity of historical housing series for other French cities stands in contrast to the abundance of sources and work on the Parisian housing market. Nevertheless, in the last few decades, there has been a significant effort to extend the quality of available information on the housing market to the rest of France. As explained in more detail below, the *National Institute of Statistics and Economic Studies* (INSEE) has united forces with the notaries association in France to put to use the very extensive notaries' data set.

1.O.5.1 Paris

House Price Series. The *Conseil General de l'Environnement et du Developpement Durable* (CGEDD)[88] publishes a price index for residential property in the Greater Paris area. The index starts in 1200 and builds upon several different data sources. For the time period analyzed in this paper (1870-2018), the index is composed of three different series. The first part of the index (1870-1944) is based on a repeat sales index by Duon (1946) using data gathered from property registers of the local tax department. It covers apartment buildings (*maisons de rapport*) such that commercial properties, single-family houses, or apartments sold by the unit remain excluded.[89] The second part of the index (1944-1999) is based on price data for apartments sold by the unit compiled by CGEDD from the notaries' database and calculated using the repeat sales method.[90] Since data for the period before 1950 are very scarce, the gap between 1945 and 1949 was filled by linearly interpolating the data from Duon (1946) and the data for the period after 1950 (Jacques Friggit, 2002). For the post-1999 period, the index is again spliced with an index by the National Institute of Statistics and Economic Studies (INSEE) for existing apartments

87. Reba, Reitsma, and Seto, 2016.
88. Conseil General de l'Environment et du Developpement Durable, 2021.
89. Until World War I single apartments could not be sold alone.
90. In France there exist two main real estate transaction databases from the notaries: The *BIEN base*, which is mostly focused on the Paris region and is managed by *Chambre Interdépartmentale des Notaires de Paris*, and the *PERVAL France*, which covers the rest of France and is managed by the *Conseil Supérieur du Notariat*.

in Paris (Clarenc et al., 2014).[91] This index is built using transaction data from the notaries' database and a mix-adjustment hedonic approach, i.e. a hedonic index is built for various subparts of Paris, which is then aggregated using stock weights. The hedonic indices include a rich set of apartment characteristics, which include a very precise location of the apartments as well as their sizes.[92]

As mentioned above the Paris index for the period between 1944 and 1999 is based on data from the notaries' database in France, which only actually started recording transactions in 1990. However, when a transaction takes place the current price as well as the price of the previous sale are recorded in the database. This poses two problems. First, as acknowledged in Jacques Friggit (2008), the number of observations for the first years of the index is quite low, making the index more sensitive to outliers. Second, we know that the observations in the 1950s represent cases of extremely long holding periods (at least 35 years), which also introduces a strong sampling bias. Usually very long holding periods (over 30 years) are excluded from repeat sales samples, because these transactions are atypical and might signal that the properties are of poor quality or have lower than average demand (Eurostat, 2013).

The CGEDD also publishes a national house price index for France, which starts in 1936. For the 1950s the Paris index grows by more than double the national index.[93] As argued in Jacques Friggit (2008), we would expect prices in Paris to outpace the rest of the country as a result of the end of the rent control laws, which had disproportionately affected Paris. However, the difference in price growth rates still seems to be too large and, given the concerns about the quality of the Paris index in this period, we decided to construct our own house price index using an independent data source.

For the period between 1950 and 1958 we collected residential apartment sales ads from the newspaper *Le Figaro* and used them to construct a new house price series. In total we collected 1,595 observations, which contained information on asking price, size of the apartment, the *arrondissement* in which the apartment was located and further characteristics of the apartment, which are described in more detail below. We then used these data to build a hedonic house price index for Paris using the time dummy approach.[94] More precisely, we use the following model:

91. The index only focuses on existing apartments, i.e. new apartments are excluded from the sample.

92. For more details about the method please consult Clarenc et al. (2014).

93. The national index is also built using the same method as the Paris index. However, the national nature of the index means that it is built based on a larger set of observations for this period and is therefore less prone to outliers.

94. This approach has been frequently been used in the literature to build house price indices using newspaper ads (see e.g. Lyons et al (2019).

$$ln(p_{i,t}) = \alpha_0 + \delta_1 D_t + \sum_{k=1}^{21} \beta_{arrond_k} + \sum_{j=1}^{12} \beta_{rooms_j} + \alpha_{new} + \alpha_{bathroom} + \alpha_{kitchen} + u_i$$

where we regress the log asking price at time t of apartment i on a series of dummy variables indicating: the year in which the ad was posted (D_t), the *arrondissement* k, in which the apartment is located (β_{arrond_k}),[95] the number of rooms j in the apartment (β_{rooms_j}),[96] whether the apartment was new or had recently been fully renovated α_{new}, and whether the ad indicated it contained a bathroom ($\alpha_{bathroom}$) or a kitchen ($\alpha_{kitchen}$). We estimated this regression using OLS by pooling all years together, the "all-in-one" approach, and by using a rolling three-year window. From Figure 1.O.9 it becomes clear that both series are strongly correlated. In the end, we decided to use the "all-in-one" series, since it uses the largest number of observations for the regression and has, therefore, more precisely estimated coefficients. The regression results show that we explain around 73% of the variation in log prices with the set of independent variables detailed above.

In Figure 1.O.9 we compare our Paris index with the repeat sales indices for Paris from Jacques Friggit (2002). While the index from Jacques Friggit (2002) grows by more than a factor of 9, our index grows by a factor of approximately 3. As mentioned above, the small number of observations makes the index from CGEDD very sensitive to outliers for this period.[97] Therefore, we think that our series is more trustworthy for this period and decided to use it in our long-run series.

In Table 1.O.15 we summarize the series we used to build our long-run index. As mentioned above, the biggest difference with respect to the long-run series from CGEDD is that we use our own house price series for the period between 1950 and 1958, which we chain-linked to the series from CGEDD.

Rent Series. For 1870–1945, we use a rent index for Paris constructed by Marnata (1961). The index is based on a sample of 11,800 different rent contracts. Data come from lease management books from residential neighborhoods in Paris and mostly refer to dwellings of relatively high quality or more expensive housing.

For the years prior to 1949, data on rents are also available for Paris (1914–1962) from the yearbooks of the International Labour Organization (various years). As shown in Knoll (2017), the series by Marnata (1961) and the series published by the International Labour Organization (various years) are highly correlated for the years they overlap.

95. Since we also collected data for the suburbs Levallois and Neuilly, we added them as the 21st *arrondissement*. The results almost do not change if we do not include them.

96. Here we considered number of rooms to be the sum of bedrooms (*chambres*), living rooms (*living*), dining rooms (*salle a manger*) and receptions (*entrée*).

97. The notaries' database is not generally available to researchers and, as such, we did not have access to the data. Therefore, we could not test whether our data concerns could actually be biasing the series from CGEDD.

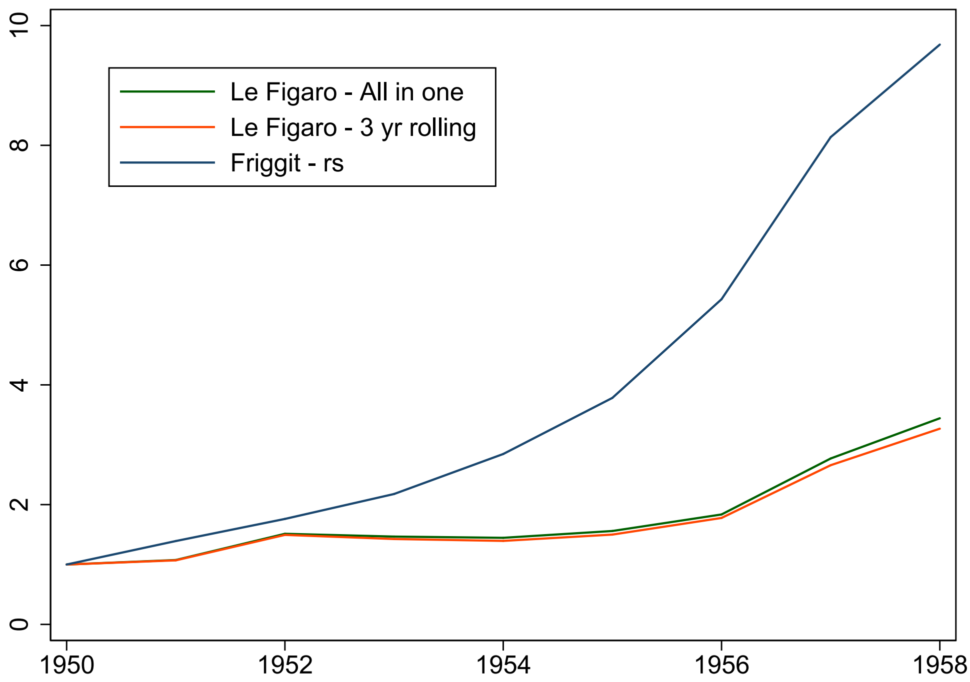

Figure 1.O.9. Nominal house price indices for Paris, 1950=1

After 1946, we rely on the rent component of the CPI for Paris from various editions of the *Annuaire Statistique de la France* published by the INSEE and which were assembled by Jaques Friggit.[98] The index covers tenants' rents only, i.e. imputed rents of owner-occupiers are excluded. After 1989 we use the mean rent per square meter of apartments in the city of Paris, considering only the estimates for the inner city, i.e. the *arrondissements*, from the *Observatoire des Loyers de l'Agglomeration Parisienne* (OLAP). This series was also assembled by Jaques Friggit and the data can be found in the yearly reports of OLAP.[99]

For the period after 1989, the INSEE has also been publishing a rent index for the region of Paris. As shown in Jaques Friggit (2013), the OLAP and the INSEE series differ in this period, with the OLAP series growing slightly more than the one from INSEE. Since our house price series focuses on the city of Paris, i.e. it excludes the outskirts, we have decided to use the series from OLAP.

Rental Yield Series. Our main benchmark for Paris is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to the alternative benchmark we collected for 2018 from *Numbeo.com*. Applying the rent-price ap-

98. More precisely, the component *loyers et charges* of the CPI was always published separately.
99. Observatoire des Loyers de l'Agglomeration Parisienne, various years.

Table 1.O.14. Final house price index for Paris

PERIOD	SOURCE	DESCRIPTION
1870-1949	Conseil General de l'Environment et du Developpement Durable (2021)	*Type(s) of dwellings*: Apartment buildings; *Type of data*: Transaction prices from tax department; *Method*: Repeat sales method.
1950-1958	Own compilation	*Type(s) of dwellings*: Apartments; *Type of data*: Asking prices from *Le Figaro*; *Method*: Hedonic time-dummy index.
1959-1999	Conseil General de l'Environment et du Developpement Durable (2021)	*Type(s) of dwellings*: Apartments; *Type of data*: Transaction prices from the notaries' database; *Method*: Repeat sales.
2000 - 2018	Conseil General de l'Environment et du Developpement Durable (2021)	*Type(s) of dwellings*: Existing apartments; *Type of data*: Data from the notaries' database; *Method*: Mix-adjusted hedonic house price index.

Table 1.O.15. Final rent price index for Paris

PERIOD	SOURCE	DESCRIPTION
1870-1945	Marnata (1961)	*Type(s) of dwellings*: Apartments; *Type of data*: Rental data from lease management books; *Method*: Chain index of repeat rents.
1946-1988	INSEE (various years)	*Type(s) of dwellings*: All types of residential dwellings; *Type of data*: Rental data from survey; *Method*: Average based on repeated rental contracts.
1989-2018	Observatoire des Loyers de l'Agglomeration Parisienne (various years)	*Type(s) of dwellings*: Apartments; *Type of data*: Rental data from survey *Method*: Average rent per square meter.

proach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.10.

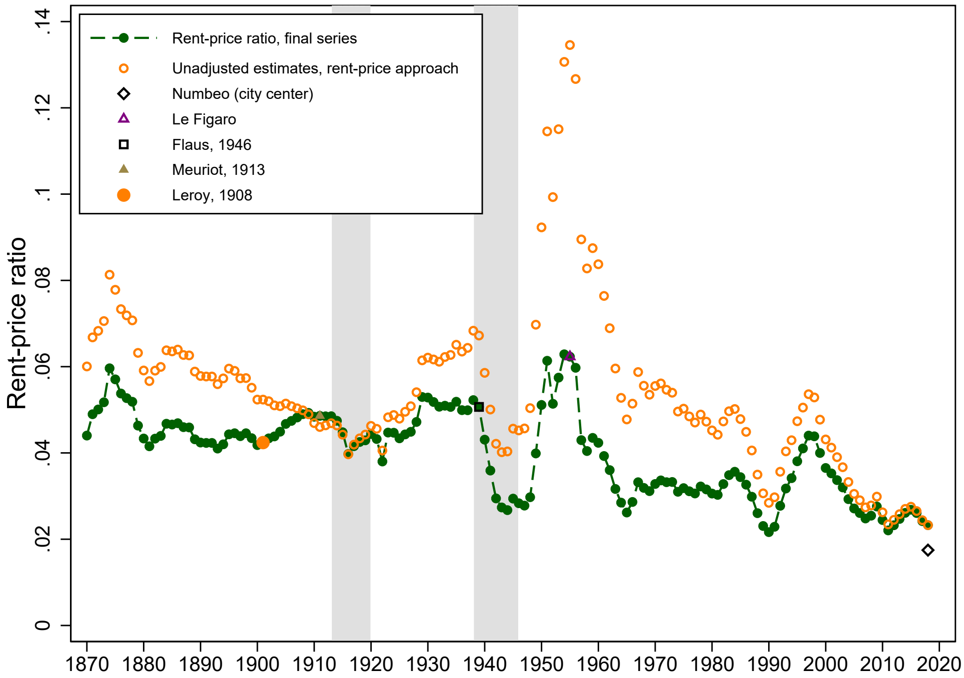

Figure 1.O.10. Paris: plausibility of rental yields

As can be seen in Figure 1.O.10 our final series diverges substantially from the unadjusted series in the 1950s. As was mentioned above, in the 1950s the rent controls were gradually abolished in Paris. The rent CPI component that we are using for this period probably does not fully capture the effect of new rentals in the market, which were not capped by the law. As a result our rent series grows substantially less than the price series, which includes almost exclusively apartments, which were no longer affected by the rent freeze law of 1948. To correct the resulting bias on our rental yield series we collected several different historical benchmarks, which we describe below.

For the year 1894 Saint-Genix et al. (1895) estimates that the total value of rents is 819 million francs while the market value of the housing stock is 13000 million francs, which produces a gross rental yield of 6.3%. Since the author does not provide many details about how the values were estimated we do not use this benchmark. For the year of 1901 Leroy-Beaulieu (1908), using data on average residential rent and house prices from *Le Livre Foncier de Paris, 1902*, estimates an average gross rental yield of 6.36%, average maintenance costs and taxes of 36.5%, and which gives an average net rental yield of 4.04%. For the year 1911 Meuriot (1913), using data on average residential rent and house price from *Le Livre Foncier de Paris, 1911*, estimates an average gross rental yield of 6.58%, and average maintenance costs and taxes of 26.1%, which gives an average net rental yield of 4.86%. Simonnet, Gallais-Hamonno, and Arbulu (1998) estimate that the gross rent of residential properties purchased by the property investment fund La Fourmi Immobiliere in Paris represented about 6 to 7 percent of property value between 1899 and 1913, which corroborates the estimates by Leroy-Beaulieu (1908) and Meuriot (1913). For the year 1939 Flaus (1946) estimates an average gross rental yield of 7.6% for the city of Paris. For the year 1955 we collected 28 ads from *Le Figaro* for apartment buildings (*maisons de rapport*) in the center of Paris, which reported both the asking price and the gross rental income of the building. By assuming total costs of one third of the gross rental income we arrive at an estimate of 6.2% net rental yield. Adjusting our rental yield series to the historical benchmarks gives us the adjusted final rental yield series—the green-circled line in Figure 1.O.10.

1.O.6 Germany

The list of the largest cities in Germany in 1900 is in descending order: Berlin, Hamburg, Dresden, Leipzig, Munich, Cologne, Wroclaw and Frankfurt.[100] Of these cities, only Berlin and Hamburg hit the 1% target. The area of Germany, however, changed drastically several times after 1900. This means that we do not include Wroclaw, which does not belong to Germany nowadays or Leipzig and Dresden, which were part of Eastern Germany between 1945 and 1990 and hence price and rent data are missing for a considerable time period. From the remaining cities, there does not exist sufficient data coverage for Munich. To still get close to the 10% target and as Germany covered a considerably larger area in 1900 compared to today, we chose to include all other cities up to and including Frankfurt in our sample. In 1950, the population in both Frankfurt and Cologne was above 1% of Germany's total population.

To the best of our knowledge, there do not exist compiled house price or rent indices on city-level in Germany from public sources. The only readily-available city-level indices we know of are from private companies like *Bulwiengesa*. Recently, researchers started to rely on asking price data from online marketplaces like *ImmoScout24* to analyze German housing markets on a local level. An impressive example is Ahlfeldt, Heblich, and Seidel (2021), who use these data to compile house price and rent indices on arbitrary local levels in Germany between 2007 and 2018. By nature, these data, however, only cover the last one or two decades. As described in the main paper, we construct a novel city-level house price and rent data set for Germany using market reports of the German Real Estate Association (IVD) and one of its predecessors.[101] These market reports surveyed local real estate agents and collected city-level observations for various market and quality segments. We will partly rely on these data to construct our German city long-run series.

There is, however, an alternative source for house price data in Germany. Since 1960, notaries in Germany are obliged to report purchase details for every real estate transaction to the so-called *Gutachterausschüsse* (GA). The GA are comprised of real estate professionals and are organized on city-level. The GA store the transaction price information, along with house characteristics, and compile annual statistics on transaction volumes and price trends that are used to calculate benchmark land prices (*Bodenrichtwerte*) and form the basis for the assessment of real estate values for bank loans and insurance purposes. The underlying micro-data in the archives of the GA cover the universe of real estate transactions in (West-)Germany over the past 60 years. So far, this micro-data has not been digitized for academic research. Recently, we started a project that aims to do this. In the course of this

100. City-level population data are taken from Reba, Reitsma, and Seto (2016) and country-level population data from Jordà, Schularick, and Taylor (2017).
101. The *Immobilienverband Deutschland (IVD)* and the predecessor *Ring deutscher Makler (RDM)*.

project, we are cooperating with the GA in Berlin, Frankfurt and Cologne. These kindly enabled us to use parts of their data to construct hedonic house price indices, which we used to construct our city-level long-run series. We will describe these indices in more detail below.

1.O.6.1 Berlin

House Price Series. For Berlin, we are able to use micro-level house price data from the GA Berlin from 1965 onward. For the period 1958 to 1965 the GA Berlin published data on average price per transaction. Before this period, we had to rely on various statistical publications. Using these we build stratification indices by housing type or district whenever possible. We provide more details below. Due to the special history of Berlin, we only use data on West Berlin after World War II. In the period when Germany was divided only data for West Berlin are available. Afterwards, house prices in East Berlin followed a considerably different trend compared to house prices in West Berlin, mainly because they started at a considerably lower level in 1990. It took a long period for prices in East and West Berlin to converge and conversion might not even be completed today. To not confound our long-run indices with these conversion effects we only use data on West Berlin also after 1990. Prior to the separation of Berlin, the city developed similarly to other cities and there was no fundamental difference between East and West Berlin. As the separation was unforeseen prior to and during World War II, we rely on the data for all of Berlin prior to 1945.

The GA Berlin kindly provided us with transaction-level data for single- and multi-family houses. These data cover the universe of all normal housing transactions in (West) Berlin that were considered to be market prices.[102] We construct separate hedonic indices by housing type (single- or multi-family housing) and eight districts ("*Bezirk*") in West Berlin.[103] We were able to rely on 28,710 transactions for multi-family houses and 63,416 transactions for single-family houses.

To calculate the indices we closely follow the methodology in Eurostat (2013). The final index is constructed in three steps: First, double imputation hedonic indices are calculated separately for single-family and multi-family houses and separated by district. Chaining is used to connect different years. All hedonic regressions use lot area, state of repair and type of building as exogenous variables. Regressions from 1980 onward also control for floor area[104] interacted with state of repair

102. The GA cleaned the data for non-market price transactions, for example transactions between family members. We also cleaned the data for all cases when not the whole building was sold.
103. We reconstructed the parts from *Bezirk* 1 and 2 that belonged to West Berlin as discrete districts. For multi-family houses the index for district 5 only starts in 1975, as we did not have enough observations before. For single-family houses we were not able to construct indices for districts 1 and 2, as there have not been enough transactions and the index for district 7 only starts in 1970.
104. Before there have been too many missing observations.

as a proxy for the quality-adjusted structure. Regressions for multi-family houses from 1980 onward do not use type of building as control anymore,[105] but instead a dummy variable indicating if a part of the building is in commercial use. All regressions are performed using maximum likelihood and assuming normally distributed standard errors. Second, for both housing types separately a Fisher-type stratification index is built from the district-level indices using chaining and transaction value shares as weights. Lastly, the final index is obtained by stratification of the respective indices for single-family and multi-family houses. We again use transaction value shares as weights.

For the period from 1870 to 1918 and 1936 to 1938 we use data from various volumes of the statistical yearbooks of Statistics Berlin[106] as done in Knoll, Schularick, and Steger (2017). The yearbooks contain aggregated data on number of sales and sales volumes for all sales of developed land. In contrast to Knoll, Schularick, and Steger (2017), we use the data on 16 to 21 districts ("*Stadtteile*") for the period from 1870 to 1906 and 1936 to 1938. With this more fine-grained data we build Fisher-type chained stratification indices following Eurostat (2013) using mean price per sales within each stratum. In this way we are able to control for locational shifts in real estate sales. To the extent that building types and locations are correlated, this approach indirectly also controls for shifts in the mix of building types reducing sample selection bias further. For the period from 1907 to 1918 we had to rely on the average price per sale in the former city of Berlin,[107] as data by district were no longer available. We match the index from 1918 to 1936 using the average sales price for the former city of Berlin using the borders of 1918.

We imputed the years in between from two sources: We rely on estimates for the price of rental apartment buildings in Prauser (1941) for the period between 1923 and 1935. For the years 1935 to 1936 we collected the average price per square meter of developed land in the city of Berlin from the statistical yearbooks of German cities.[108] For the period directly after World War I and the period of German hyperinflation no data were available. For the years 1938 to 1940 we collect the average price per square meter of developed land from another publication of Statistics Berlin.[109]

During World War II no house price data are available for Berlin. The earliest data after World War II we found start in 1953. From 1953 to 1955 we again rely on a publication by Statistics Berlin.[110] The data cover number of transactions and

105. The reasons are multicollinearity with floor area and too many degrees of freedom relative to the number of observations.
106. "Statistisches Jahrbuch der Stadt Berlin".
107. Which is nowadays the city-center of Berlin.
108. See Knoll, Schularick, and Steger (2017) data appendix.
109. "*Berlin in Zahlen*" (Volume 1942, p. 86).
110. "*Berliner Statistik*" (Volume 1958, p. 118).

transaction volume in 20 districts in West Berlin.[111] We again build a Fisher-type stratification index as describes above. For the years 1955 to 1958 we use aggregate data from Pistor (1957) and Pistor (1960). We use the data on sales per housing category (single/multi-family houses, which are not rental apartment buildings, and rental apartment buildings) to again build a Fisher-type stratification index. We also use the data on sales per district for 1958 from the same source to link 1958 to 1938 using stratification per district for all districts belonging to West Berlin.

To fill the remaining gap between 1958 and 1965 we use data from Berger (2010). Again we have to rely on aggregates for all of West Berlin. From 1958 to 1960 we use the average price per transaction for all developed lots without destroyed buildings ("*Trümmergrundstücke*"). For the period from 1960 to 1965 we instead rely on data on price per sold apartment, because apartments are a much more homogeneous good compared to developed lots and the resulting index is, therefore, less volatile. Table 1.O.16 summarizes the components of our final house price index.

Rent Series. The rent index for Berlin is constructed using multiple data sources. Starting in 1975, we use the data we constructed from market reports of the German Real Estate Association and its predecessor. Before, we rely on a rent index calculated during the process of constructing a city-level CPI index. Prior to World War II, we additionally use legal rents in years with strict rent freezes. Prior to and during World War I, we instead rely on rent data collected for tax reasons and published by Statistics Berlin. We provide more details below.

The construction of rent indices from the real estate market reports is described in the Appendix of the main paper. We use the index for Berlin from 1975 onward. This index covers only West Berlin until 2013. From 2014 onward, only data for all of Berlin are available. Rents in West and East Berlin had, however, already come very close in 2013, such that the trends can be assumed to be the same in West and East Berlin after 2013.[112]

For the period from 1950 to 1975 and 1934 to 1938 we use rent indices constructed for the city-level CPI calculation for Berlin from statistical yearbooks published by Statistics Berlin.[113] For the period from 1950 onward the index is intended to track flats for a four-person blue-collar worker household (excluding heating and

111. In contrast to the data used for the earlier periods, these data do not only cover sales, but all kinds of real estate transactions. This probably increases measurement error. For this reason we only use these data source for two years, when no other data was available, and make the link from before to after World War II using the data for 1958.

112. We construct the index by chaining and compare the aggregate data in 2014 with the aggregates from West and East Berlin in 2013, such that the sample is always the same comparing consecutive years.

113. "*Statistisches Jahrbuch Berlin*" (Volume 1952-1976) and "*Statistisches Jahrbuch der Stadt Berlin*" (Volume 1935-1939).

Table 1.O.16. Final house price index for Berlin

PERIOD	SOURCE	DESCRIPTION
1870 - 1906	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated by district from yearbooks; *Method*: Stratification.
1907-1918	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated for former city from yearbooks; *Method*: Average price per transaction.
1923-1935	Prauser (1941)	*Type(s) of dwellings*: Rental apartment buildings; *Type of data*: Price estimates; *Method*: Price per transaction.
1935-1936	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated for former city from yearbooks; *Method*: Average price per square meter of developed land.
1936-1938	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated by district from yearbooks; *Method*: Stratification.
1938-1940	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated for former city from yearbooks; *Method*: Average price per square meter of developed land.
1953-1955	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All transactions aggregated by district from yearbooks; *Method*: Stratification.
1955-1958	Own compilation	*Type(s) of dwellings*: Single/multi-family houses and rental apartment buildings; *Type of data*: All sales aggregated by two housing categories; *Method*: Stratification.
1958-1960	Berger (2010)	*Type(s) of dwellings*: All developed lots except destroyed ones; *Type of data*: All sales aggregated for West Berlin; *Method*: Average price per transaction.
1960-1965	Berger (2010)	*Type(s) of dwellings*: All sold apartments; *Type of data*: All sales aggregated for West Berlin; *Method*: Average price per transaction.
1965-2018	Own compilation	*Type(s) of dwellings*: Universe of single-family and multi-family houses; *Type of data*: Transaction-level data kindly provided by the Gutachterausschuss Berlin; *Method*: Stratified hedonic index.

other costs) and covers West Berlin.[114] For the period prior to World War II, the in-

114. The method or sample to construct the index did, however, change in between, such that different publications give slightly different results for the years 1962 to 1964. We rely on the index given in 1958=100 until 1964.

dex covers only old flats (also excluding heating and other costs) for which rent controls applied. The rent index in 1951 is given in 1938 values, such that the linking of the two periods is straightforward.

For the period between 1924 and 1933 we directly rely on legal rents from statistical yearbooks.[115] During this time period, legal authorities dictated a strict rent ceiling in terms of 1914 rents ("*Friedensmiete*"). As this rent ceiling was typically set very low and housing was scarce during this time period, legal rents can be assumed to have been binding in large cities like Berlin. Moreover, for the period from 1934 to 1938, the CPI rent index and legal rents show exactly the same patterns. One drawback is that new construction was excluded from the rent ceiling. There are, however, no other rent data available for this period of time. Both legal rents as well as the CPI rent index for 1934 to 1938 are given in 1914 values, such that linking is straightforward. For the period from 1918 to 1923 no reliable data exist.

For the period from 1870 to 1917 we rely on average rents of the universe of all rented units collected for tax reasons and published in statistical yearbooks.[116] For the period from 1870 to 1907, averages are given by 21 districts ("*Stadtteile*"). As done for house prices, we use these disaggregated data to build Fisher-type chained stratification indices following Eurostat (2013). This way, we are able to control for locational shifts in the sample of rented units. For the period between 1908 to 1917, only averages for the entire city are given, such that we cannot control for locational shifts. For the period before, however, the index controlling and not controlling for locational shifts are similar. One disadvantage of this data source is that it also contains commercial rooms. Therefore, we additionally rely on data from housing censuses between 1880 and 1905, which was collected in five year steps, published in Reich (1912). These data covers the universe of all rented residential apartments in Berlin and contain average rent by number of heated rooms. We construct rent increases in five year steps using average rent weighted by the number of apartments with the respective number of rooms from the 1880 census.[117] We use these data to adjust rent increases between 1880 and 1905 and use the rent index from tax data only for interpolation and extrapolation. For the period for which both sources exist, however, five-year increases from both sources are very similar.

Table 1.O.17 summarizes the components of our final rent index.

Rental Yield Series. Our main benchmark for Berlin is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to all alternative benchmarks we collected for 2018, especially the ones by *Numbeo.com* and the GA (see below). Applying the rent-price approach to our main benchmark gives us

115. "*Statistisches Jahrbuch der Stadt Berlin*" (Volume 1925-1935).
116. "*Statistisches Jahrbuch der Stadt Berlin*" (Volumes 1877-1917).
117. From "*Statistisches Jahrbuch der Stadt Berlin*" (Volume 1883).

Table 1.O.17. Final rent index for Berlin

PERIOD	SOURCE	DESCRIPTION
1870-1907	Own compilation	*Type(s) of dwellings*: All residential apartments and commercial rooms for rent; *Type of data*: Averages by district collected for tax purposes from yearbooks; *Method*: Stratification (only used for interpolation and extrapolation).
1880-1905	Own compilation	*Type(s) of dwellings*: All residential apartments for rent; *Type of data*: Averages by number of rooms from census from yearbooks; *Method*: Average weighted by number of flats in 1880.
1908-1917	Own compilation	*Type(s) of dwellings*: All residential apartments and commercial rooms for rent; *Type of data*: Averages for entire city collected for tax purposes from yearbooks; *Method*: Average rent.
1924-1933	Statistics Berlin	*Type(s) of dwellings*: Apartments in old buildings subject to rent control; *Type of data*: Legal rent; *Method*: Legal rent in 1914 values.
1934-1938	Statistics Berlin	*Type(s) of dwellings*: Apartments in old buildings subject to rent control; *Type of data*: From CPI-construction; *Method*: CPI rent index.
1950-1975	Statistics Berlin	*Type(s) of dwellings*: Apartments for four-person blue-collar worker household; *Type of data*: From CPI-construction; *Method*: CPI rent index.
1975-2018	Own compilation	*Type(s) of dwellings*: Apartments; *Type of data*: New contract rents by construction period and housing quality reported by local real estate agents; *Method*: Matched model approach using mode prices by quality and construction period bins.

the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.11.

To verify the historical rental yield series, we collected alternative benchmarks from three different sources. First, we use benchmarks from the market reports of the *German Real Estate Association* (IVD). These market reports directly report mode price-rent ratios for residential investment buildings from 1989 onward. The Appendix in the main paper describes how we calculate net rental yields given these. The resulting rental yield benchmarks are plotted as purple triangles in Figure 1.O.11. This series is somewhat above our long-run series, but shows similar (cyclical) patterns. Moreover, the earliest values from the IVD series are very close to our long-run series.

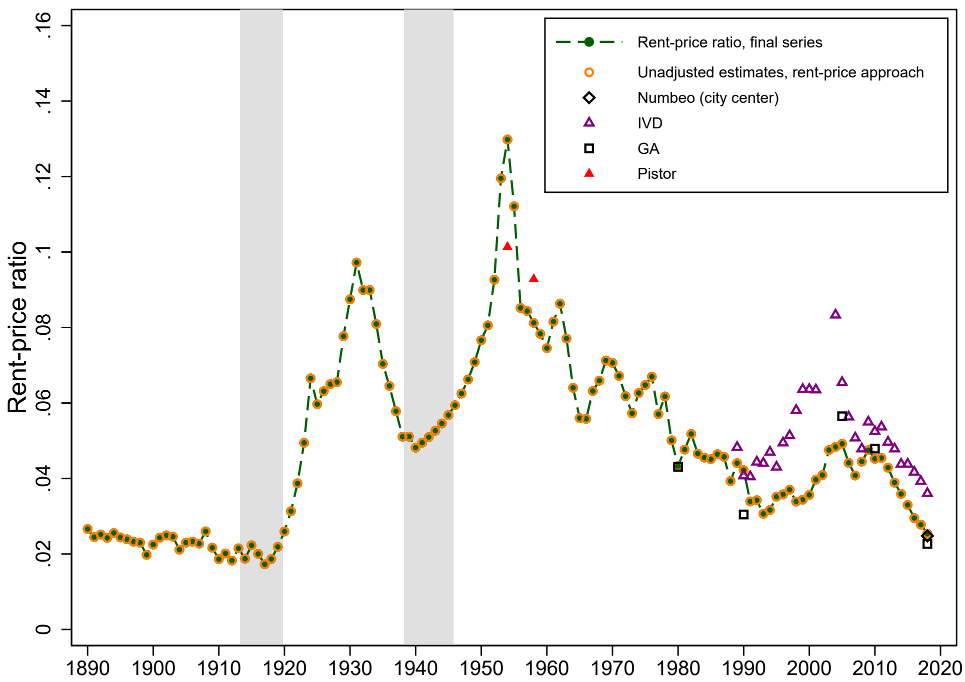

Figure 1.O.11. Berlin: plausibility of rental yields

Second, in their yearly market reports, the GA publishes price-rent ratios for investment buildings. [118] For the years 1980 and 1990, rent values still contain running costs, which needed to be paid by the renter.[119] We assume 20% of rents are running costs to calculate gross rental yields.[120] Following Jordà et al. (2019) we subtract one third of these to get net rental yields. The resulting benchmarks are depicted as black squares in Figure 1.O.11. These benchmarks are very close to our long-run rental yield series, especially the earliest benchmark in 1980. We use the 2018 benchmark from the GA as our alternative benchmark in the robustness section of the main paper, because it has the broadest coverage and relies on micro-data of actual transaction prices. This benchmark is very close to the benchmark from Numbeo.com used as an alternative benchmark for some of the other cities.

118. For 2010 and 2018, we take the average of all investment buildings. For earlier years, we take the average of the price-rent ratio ranges for buildings constructed after 1924. For earlier construction periods, large investments into maintenance might have been necessary. Therefore, we exclude these.
119. For example costs for water or waste disposal ("*Bruttokaltmiete*").
120. We use the micro-level data from the GA to estimate the relation between rent-price ratios with and without running costs for the years between 1995 and 2000. For these years, running costs are between 20 and 25% of rents. As a conservative estimate, we assume that 20% of rents were running costs before 1995.

Third, Pistor (1955) and Pistor (1960) state rent-price ratios for investment buildings in 1954 and 1958. Again, running costs are still included in rent payments and we assume that these have been 20% of rents. The resulting net rental yields are plotted as red triangles in Figure 1.O.11. Both values are reasonably close to our long-run rental yield series.

To summarize, all benchmark values we collected are close to our original rental yield series. Moreover, some benchmarks are above this series and others below. As rental yield benchmarks are subject to measurement error by themselves, we do not adjust our rental yield series for Berlin to any benchmarks.

1.O.6.2 Cologne

House Price Series. The GA in Cologne kindly provided us with micro-level house price data starting in 1989 for all housing types and starting in 1981 for apartments. We use these data to build hedonic house price indices. For the period from 1966 to 1981, we were able to use a subsample of micro-level house transactions from archived data from the GA, which we use to construct a repeat sales index. For the period before 1966, we had to rely on average price per transaction from statistical publications as no other data were available to us. Before World War II, statistical publications contain the average price by district, such that we are able to build stratification indices. We provide more details below.

To construct the hedonic index starting in 1989 we use transaction-level data provided by the GA Cologne. These data cover the universe of transactions for all single-family and multi-family houses as well as apartments that can be assumed to have sold for market prices.[121] We use cleaned transaction prices provided by the GA. These values adjust for sales conditions unrelated to the property itself, for example if the inventory or a kitchen was sold with the house or if specific rights were still granted to the seller. We construct separate hedonic indices by housing type (single-family housing, multi-family housing or apartments) and nine districts ("*Stadtbezirke*") for apartments, eight districts for single-family-houses,[122] and three parts of the city for multi-family-houses.[123] We clean the data for duplicates,[124] out-

121. Clear non-market-price transactions, for example sales between family members, have been excluded by the GA from the sample.
122. We excluded the city-center district ("*Innenstadt*"), because nearly no sales of single-family houses occur in this district.
123. As the number of multi-family houses transacted is considerably lower than for the other types, we aggregates the district to three parts: city center ("*Stadtbezirk Innenstadt*"), districts left of the Rhine ("*Stadtbezirke*": "Chorweiler", "Nippes", "Ehrenfeld", "Lindenthal", and "Rodenkirchen") and districts right of the Rhine ("Stadtbezirke": "Mülheim", "Kalk", and "Porz").
124. For apartments we also delete all duplicates in address, sales price and transaction year, because we want to exclude package deals.

liers in sales prices as well as outliers in the (non dummy) dependent variables.[125] After this procedure, we are able to rely on 12,538 transactions for multi-family houses, 37,972 transactions for single-family houses and 131,744 transactions for apartments.

To calculate the indices we closely follow the methodology in Eurostat (2013). The final index is constructed in three steps: First, double imputation hedonic indices are calculated separately for single-family and multi-family houses and separated by district or part of city. Chaining is used to connect different years. Hedonic regressions for single-family houses use lot area as dependent variable.[126] After 2010, a dummy is additionally included, which controls for houses being detached or attached. Hedonic regressions for multi-family houses use lot area and a dummy for commercial use as exogenous variables.[127] To construct the index for apartments, hedonic regressions use area of the apartment,[128] and a dummy for whether the flat is newly constructed.[129] From 2010 onward, a dummy is included for whether the flat is in a high-rise building (more than ten floors).[130] Starting 2015, we additionally control for quality of the location ("*Lagequalität*"), which was estimated by the GA in four categories.[131] All regressions are performed using maximum likelihood and assuming normally distributed standard errors. Second, for all three housing types separately a Fisher-type stratification index is built from the district-level/part-level indices using chaining and transaction value shares as weights. Lastly, the final index is obtained by stratification of the respective indices for single-family houses, multi-family houses and apartments. We again use transaction value shares as weights. Trends for the indices covering different housing types are very similar.[132]

125. For multi-family houses, we also clean the data for buildings with a large number of floors (more than ten) for all non-missing observations to exclude high-rise buildings. These buildings are rarely transacted and will follow a considerably different pricing compared to other multi-family houses. We assume that for all high-rise buildings the number of floors is non-missing as this variable is of considerably more importance for these buildings.

126. Before 1992, we do not use any dependent variables, as we have too many missing observations for lot area. In consequence, for the first three years, the single-family-house index is in fact a stratification index.

127. All other variables have many missing observations; before 1992, hedonic regressions do not use any dependent variables, such that the multi-family house index is in fact a stratification index for these three years.

128. Observations with extreme or missing values are excluded.

129. The dummy is equal to one if the apartment is less than two years old at the point of sale or marked as "*Neubau*" (new construction).

130. Before, the number of floors of the building is missing for nearly all apartments.

131. The GA defines four quality bins ("*einfach*", "*mittel*", "*gut*" and "*sehr gut*"), which we include as factor variables. Quality of the location does not differ much within districts, such that excluding it from the regression has has no visible effect on the overall index.

132. See Appendix of the main paper.

For the period between 1981 and 1989 only the data for apartments for the first four districts of Cologne are available,[133] which covers 7,600 observations. We use this data to construct hedonic indices separated by district as described above and use stratification with transaction value shares as weights to aggregate the indices for the four districts.

In their archives, the GA Cologne has very detailed maps which show transaction prices and year of sale by address. We use these maps for central parts of the city to extract sales prices for houses before 1989. Unfortunately, the number of transactions marked on these maps decreases for earlier years. Moreover, extracting transaction prices and addresses from maps requires a considerable amount of manual labor. Consequently, the number of observations per year is considerably below the number for the micro-level data we use after 1989.[134] We match the resulting transaction-level data with the data on housing sales after 1990 to build a repeat sales index. Our data features on average 25 matched observations per year between 1966 and 1989. To build the repeat sales index we follow Eurostat (2013) and adjust for heteroscedasticity in standard errors using the weighted least squares (WLS) approach suggested by Case and Shiller (1987). As the number of observations per year used to build the repeat sales index is low, we use the hedonic index for apartments described above after 1981. Both indices, however, follow a similar trend.

Between 1948 and 1975, Statistics Cologne published aggregated data on lot sales for the city of Cologne in the statistical yearbooks.[135] Between 1948 and 1958, we use the average price for a developed lot in the city of Cologne. Between 1959 and 1972, the yearbooks only contain averages for developed and single undeveloped lots prepared for construction ("*Einzelbaustellen*") pooled together. Only after 1972, are statistics again published separately for developed lots. As prices of developed and undeveloped lots might have featured different time trends, we calculate the total increase for developed lots only between 1958 and 1973 and use the average transaction price of the pooled series only to interpolate the index between these years. We use the resulting index only until 1966, when the repeat sales index becomes available.

Prior to World War II, we rely on various publications by Statistics Cologne.[136] These contain aggregate data for transaction volume, area and numbers of sales

133. For this period, apartment data only exist for the districts "Innenstadt", "Rodenkirchen", "Lindenthal", and "Ehrenfeld". In the apartment data between 1989 and 2018 the first four districts cover 58% of all transactions.

134. We were able to extract 1,577 observations between 1966 and 1988.

135. "*Statistisches Jahrbuch der Stadt Köln*" (Volumes 1948-1957).

136. "*Statistisches Jahrbuch der Stadt Köln*" (Volumes 1948-1957) and "*Cölnische Statistische Vierteljahreshefte*" (Volumes 1906-1913).

of developed lots by district.[137] We use the average price per square meter of developed lots to build Fisher-type chained stratification indices following Eurostat (2013) for the period from 1904 to 1941.[138] This way, we control for locational shifts in the sample of sold lots as well as for changes in the average lot size. For the years from 1902 to 1904, we had to rely on the average price per transaction of developed lots within the entire city of Cologne from Neuhaus (1916).[139] We match the data between 1941 and 1948 using the average price per transaction of developed lots within the entire city.

Table 1.O.18 summarizes the components of our final house price index.

Rent Series. As done for Berlin, we use a rent index constructed from market reports of the German Real Estate Association and its predecessor for the most recent period. Before, we use either data from CPI index construction or from other statistical publications. In contrast to Berlin, however, historical rent data for Cologne is less reliable, because it either covers only a subset of the rental market within Cologne or a broader region than just the city of Cologne. To minimize resulting biases in our long-run rent index, we use data from housing censuses in 1890, 1910, 1918, 1950, 1956, 1968 and 1987 to adjust our rental index. The yearly data sources are only used to interpolate the resulting index between census years. This procedure ensures that the trend in our rent index reproduces the rent development of the entire rental market within Cologne, because it minimizes sample selection biases, while the detailed census data also enable us to use standard quality controls.

The data from housing censuses cover the universe of all rented residential units within Cologne. They are taken from various statistical publications.[140] These sources typically report average rent disaggregated by number of rooms, construction period and sometimes even district. We calculate increases between consecutive census years using Fisher-type stratification following Eurostat (2013). Calculating these increases does, however, pose two challenges. First, the way of aggregating and reporting the data changed between census years, such that straightforward matches are not always possible. Second, the city of Cologne grew over time,

137. For 1904 and 1905 the data is aggregated by four parts of former Cologne ("Altstadt", "Neustadt", "innere Vororte", and "äußere Vororte"; between 1906 and 1912 13 districts are covered, between 1913 and 1929 sixteen districts and afterwards again thirteen, because three were merged with their neighboring districts.
138. For consecutive years, during which the number of districts/parts change, we aggregate the data for the more detailed year, such that we can build a chained stratification index for the same areas between both years.
139. We collected the number of transactions from statistical yearbooks.
140. 1890, 1910: Neuhaus (1915); 1918: "*Statistisches Jahrbuch Köln*" (Volume 7, 1919); 1950: "*Statistische Mitteilungen der Stadt Köln*" (1955); 1956: "*Statistische Mitteilungen der Stadt Köln*" (1958); 1968: "*Statistisches Jahrbuch Köln*" (Volume 56, 1969); 1987: "*Sonderreihe zur Volkszählung 1987 in Nordrhein-Westfahlen Band Nr. 6.1.*".

Table 1.O.18. Final house price index for Cologne

PERIOD	SOURCE	DESCRIPTION
1902-1904	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated for former city from statistical publications; *Method*: Average price per transaction.
1904-1941	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated by district from statistical publications; *Method*: Stratification.
1948-1966	Own compilation	*Type(s) of dwellings*: All developed (and undeveloped) lots; *Type of data*: All sales aggregated for former city from yearbooks; *Method*: Average price per transaction (the series containing undeveloped lots is used for interpolation only).
1966-1981	Own compilation	*Type(s) of dwellings*: Houses in central locations; *Type of data*: Transaction-level data from archived maps from the Gutachterausschuss Cologne; *Method*: Repeat-sales index.
1981-1989	Own compilation	*Type(s) of dwellings*: Universe of sold apartments in the first four districts of Cologne; *Type of data*: Transaction-level data kindly provided by the Gutachterausschuss Cologne; *Method*: Stratified hedonic index.
1989-2018	Own compilation	*Type(s) of dwellings*: Universe of single-family houses, multi-family houses and apartments; *Type of data*: Transaction-level data kindly provided by the Gutachterausschuss Cologne; *Method*: Stratified hedonic index.

both by extending its borders spatially and by a high level of new construction. To compare like with like, we always only compare consecutive census years and additionally try to exclude all buildings that were not part of the earlier census year. We provide more details below.

To calculate the stratification increase between 1890 and 1910 we use data disaggregated by number of rooms (1-4) and three parts of the city.[141] Using this stratification, we are able to control for the size of the flat and the rough location. We are not able to exclude buildings constructed after 1890, but as we control for the most relevant quality changes and the two census years are only 20 years apart, we think that this does not bias the result considerably. The data from the census in 1918 are only disaggregated by number of rooms, such that we can only stratify by the size of the dwelling between 1910 and 1918.[142] The census data from 1950 are

141. "Altstadt", "Neustadt" and "Vororte".

142. This can only be taken as an approximation, because the city of Cologne grew in space between 1910 and 1918. To the best of our knowledge there are, however, no better data available for 1918.

given by number of rooms and building period. To calculate the increase between 1918 and 1950, we only rely on flats built prior to 1918, such that we compare the same flats over time. Moreover, we stratify by the number of rooms to control for sample shifts in the size of flats. The data for 1956 are given by building period and district and contain rent per dwelling as well as rent per room. We calculate the increase between 1950 and 1956 using rent per room and stratifying by building period[143] using the total number of rooms as weights. This way, we control for size of the dwelling and time of construction to compare almost the same buildings over time. For 1968, the data contain the average rent per square meter by building period and district. To compare the data to 1956, we calculate the average rent per room using data for the average size of rooms from the same census year.[144] To calculate the increase between 1956 and 1968 we then only consider dwellings built prior to 1948 to exclude new construction after 1968,[145] and stratify the data by district ("*Stadtbezirk*"). This way, we compare only dwellings that already existed in both census years, control for size by taking rent per room, and control for location by stratification. The data from the 1987 census contain rent per square meter disaggregated by district. This enables us to exclude all new districts added to the city of Cologne in between.[146] To calculate the index between 1968 and 1987, we stratify the data by district and use average rent per square meter.[147] This allows us to control for size and location. We are, however, not able to control for building period, because the necessary data are missing in 1987. As we control for the most relevant quality changes over time, we assume that this does not bias the results.

Given these overall increases from the census data, we construct a yearly rent index from various sources to interpolate and extrapolate the index between census years. Starting in 1973, we use the rent data from the German Real Estate Association and its predecessor. The construction for rent indices from the real estate market reports is described in the Appendix of the main paper.

From 1948 to 1975, we have to rely on a rent index constructed for the CPI of North Rhine-Westphalia from statistical yearbooks.[148] This index tracks rents for four-person employee ("*Arbeitnehmer*") households. It covers several cities within the federal state and not only the city of Cologne. Cologne is, however, the largest city within North Rhine-Westphalia and, therefore, presumably was given a large

143. We only use building periods until 1948 in the 1956 data to exclude new construction after 1950.
144. We calculate the average size of rooms as weighted average of the average size of all rented dwellings in Cologne with x rooms divided by the number of rooms x, weighted by total size of flats with x number of rooms; source "*Statistisches Jahrbuch Köln*" (1970).
145. The data for 1968 only breaks building periods in 1948.
146. The city of Cologne grew considerably in 1975; all new districts of Cologne and districts that could not clearly be associated to an old district are dropped from the 1987 data.
147. As total number of square meters is not given by districts, we instead weight by the total number of flats by district.
148. "*Statistisches Jahrbuch der Stadt Köln*" (Volumes 1948-1973).

weight during index construction. Moreover, rent developments of neighboring cities can be assumed to be correlated with the developments in Cologne. Indeed, the overall increases are similar comparing the census data and the CPI rent index.[149]

Prior to World War II, we are able to rely on data collected for a city-level CPI index for the city of Cologne from statistical yearbooks.[150] Between 1921 and 1925 as well as 1928 and 1942, we use a rent index for working-class apartments with two rooms and a kitchen.[151] For the period from 1919 to 1921 as well as for 1926 we use the mode monthly rent (including black market) for working-class apartments with two rooms and a kitchen collected to calculate the CPI index from statistical yearbooks.[152] We interpolate the growth rate for 1927. The CPI index is given in 1914 values, such that we can link the CPI data to the data ending in 1918, correcting for the index increases between 1914 and 1918. We link the data from 1942 to 1948 using the rent increases calculated from the census data.

During World War I, *Statistics Cologne* published average rents of vacant dwellings by number of rooms and city district.[153] We use these data to build a stratification index using housing stock in 1910 as (constant) weights. This way, we can control for locational shifts as well as shifts in dwelling size for the sample of vacant apartments.

For the period between 1904 and 1913, we use market rents for vacant dwellings designed for workers ("*Arbeiterwohnungen*") published by *Statistics Cologne*.[154] The data is given by number of rooms and part of the city.[155]. We aggregate the quarterly data for all non-missing quarters to get yearly averages. We then calculate increases using Fisher-type stratification by number of rooms and part of city.

Table 1.O.19 summarizes the components of our final rent index. It first depicts the years for which census data exist. Then it describes the components of the yearly rent index. We only use the yearly index to interpolate and extrapolate between and after census years, because the yearly data do not cover the ideal sample of the entire rental market in Cologne before 1973, whereas the census data cover the universe of all rented dwellings.

149. Between 1950 and 1956, we calculate an increase of rents in Cologne from census data of a factor of approximately 1.28 and the CPI rent index for North Rhine-Westphalia increased by a factor of 1.20. For the period between 1956 and 1968 the indices increased by a factor of 2.18 and 2.03, respectively.

150. "*Statistisches Jahrbuch der Stadt Köln*" (Volumes 1921-1942).

151. 1926 and 1927 are missing from the CPI index data.

152. "*Statistisches Jahrbuch der Stadt Köln*" (Volume 1920-1926).

153. We use 14 out of 16 districts, which feature decent data coverage; source: "*Kölner Statistik 2. Jahrgang Heft 1*" (1919).

154. "*Cölnische Statistische Vierteljahreshefte*" (Volumes 1904-1913).

155. "Altstadt", "Neustadt", and "Vororte"

Table 1.O.19. Final rent index for Cologne

PERIOD	SOURCE	DESCRIPTION
1890, 1910, 1918, 1950, 1956, 1968, 1987	Own compilation	*Type(s) of dwellings*: All rented residential dwellings; *Type of data*: Census data from statistical publications; *Method*: Stratification - we use these data to adjust the trend of the overall index as described in the main text.
1904-1913	Own compilation	*Type(s) of dwellings*: Vacant rental dwellings designed for workers; *Type of data*: Average rent by part of city and number of rooms; *Method*: Stratification.
1914-1918	Own compilation	*Type(s) of dwellings*: All kinds of vacant rental dwellings; *Type of data*: Average rent by district and number of rooms; *Method*: Stratification.
1919-1921	Statistics Cologne	*Type(s) of dwellings*: Working-class apartments with two rooms and a kitchen; *Type of data*: From CPI-construction; *Method*: Mode prices.
1921-1942	Statistics Cologne	*Type(s) of dwellings*: Working class apartments with two rooms and a kitchen; *Type of data*: From CPI-construction; *Method*: CPI rent index.
1948-1975	Statistics North Rhine-Westphalia	*Type(s) of dwellings*: Apartments for four-person employee households; *Type of data*: From CPI-construction for North Rhine-Westphalia; *Method*: CPI rent index.
1973-2018	Own compilation	*Type(s) of dwellings*: Apartments; *Type of data*: New contract rents by construction period and housing quality reported by local real estate agents; *Method*: Matched-model approach using mode prices by quality and construction period bins.

Rental Yield Series. Our main benchmark for Cologne is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to all alternative benchmarks we collected for 2018. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.12.

To verify the historical rental yield series, we collected alternative benchmarks from three different sources. First, there only existed a benchmark for Cologne from *Numbeo.com* for 2015. This benchmark is below, but close to our long-run series.

Second, we use benchmarks from the market reports of the *German Real Estate Association* (IVD). These market reports directly report mode price-rent ratios for residential investment buildings from 1989 onward. The Appendix in the main

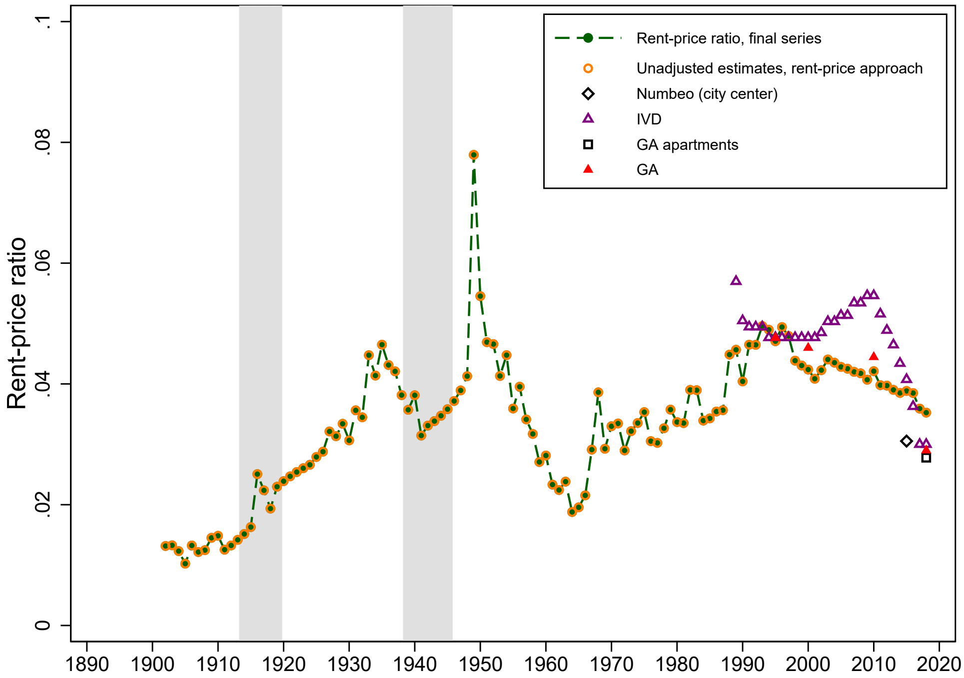

Figure 1.O.12. Cologne: plausibility of rental yields

paper describes how we calculate net rental yields. The resulting rental yield benchmarks are plotted as purple triangles in Figure 1.O.12. This series shows somewhat more cyclicality compared to our long-run series, but is overall very close in values.

Third, in their yearly market reports, the GA publishes average price-rent ratios for investment buildings.[156] Following Jordà et al. (2019) we subtract one third of these to get net rental yields. The resulting benchmarks are depicted as red triangles in Figure 1.O.12. These benchmarks are very close to our long-run rental yield series. For 2018, we also calculate rental yields for apartments given the average prices and rents per square meter provided by the GA in the yearly report. The resulting value is plotted as a black square in Figure 1.O.12 and is very close to the rental yields for investment buildings. We use this benchmark as our alternative benchmark in the robustness section of the main paper, because it has a broader coverage compared to just covering investment buildings and relies on micro-data of actual transaction prices.

To summarize, all benchmark values we collected are close to our original rental yield series. As rental yield benchmarks are subject to measurement error by them-

156. ("*Rohertragsfaktor*"); we take the average value for normal rented investment buildings ("*Mietwohnhäuser*"); in cases when only ranges are given, we take the midpoint from these ranges; source: "*Grundstücksmarktbericht für die Stadt Köln*" (2019, 2011, 2000, 1995).

selves, we do not adjust our rental yield series for Cologne to any benchmarks. We were not able to find earlier historical rental yield benchmarks for the city of Cologne. However, as the rental yield series seems to be plausible compared to other German cities and we adjust the rent series for sample selection biases in the trend using census data, we assume the resulting rental yield series to be accurate.

1.O.6.3 Frankfurt

House Price Series. The house price series for Frankfurt is constructed using data from the GA Frankfurt starting in 1982. For the period from 1960 to 1982, the GA kindly provided us access to their analogue archives, so we were able to digitize a subsample of their transaction records. Prior to 1960, we had to rely on various publications of Statistics Frankfurt. From these sources, we calculated the average transaction price per square meter of developed lots. Unfortunately, the earlier data do not allow us to control for locational shifts in the sample of transacted buildings within the city of Frankfurt.

The GA Frankfurt kindly provided us with transaction-level data for single- and multi-family houses for the period 1982 to 2018. These data cover the universe of all normal housing transactions in Frankfurt that were considered to be market prices.[157] We use cleaned transaction prices provided by the GA. These values adjust for sales conditions unrelated to the house itself, for example if the inventory or a kitchen was sold with the house or if specific rights were still granted to the seller. We construct separate hedonic indices for single-family and multi-family houses. Moreover, we calculate indices separately for five parts of the city for single-family houses and four parts of the city for multi-family houses.[158] We drop all observations that have missing prices or missing values in one of the dependent variables.[159] After this step, we use 6,093 transactions for multi-family houses and 16,237 transactions for single-family houses between 1982 and 2018.

To calculate the indices we closely follow the methodology in Eurostat (2013). The final index is constructed in three steps: First, double imputation hedonic indices are calculated separately for single-family and multi-family houses and separated by part of the city. Chaining is used to connect different years. Hedonic regressions for single-family houses use lot area as dependent variable as well as a

157. The GA cleaned the data of non-market-price transactions, for example transactions between family members.

158. We aggregate the districts ("*Ortsbezirke*") 1-4 to form the city center, district 5 forms the part "South", district 6 forms the part "West", we aggregate districts 7 to 11 to form a part in north-east, which is closer to the center, and the districts 12 to 16 as the outer north-east part. For multi-family houses, we aggregate the inner and outer parts in the north-east, because the number of observations in the outer part is very low.

159. This implies that we have to ignore a considerable part of the data set. We use a low number of only highly relevant dependent variables, in order to minimize the number of observations we have to exclude.

dummy being 1 if the house has a garage and a dummy for houses being classified as a townhouse ("*Stadthaus*").[160] After 2005, we do not use these dummies anymore, but additionally control for floor area.[161] Starting 2006, we also use dummy variables to control for type of house.[162] Regressions for multi-family houses use volume of structure ("*Bruttorauminhalt*") as exogenous variable.[163] Starting in 2005, we instead use floor area in the regressions. All regressions are performed using maximum likelihood and assuming normally distributed standard errors. Second, for both housing types separately a Fisher-type stratification index is built from the part-level indices using chaining and transaction value shares as weights. Lastly, the final index is obtained by stratification of the respective indices for single-family houses and multi-family houses. We again use transaction value shares as weights.

For the period from 1960 to 1981, we hand-collected transaction-level data from the archives of the GA. The reporting of the data changed from 1970 to 1971, so we have to use different methodology before and after 1971. For the period between 1971 and 1981, we were able to collect data on nearly all normal sales of residential houses that can be assumed to have been market prices. We clean the data of all buildings, which seem to be commercial or public, which were demolished after the transaction or which were bought to construct a road. Moreover, we also exclude transactions in which only a part of the right to the land was sold ("*ideeller Anteil*"). Again, we drop all observations that have missing prices or missing values in one of the dependent variables. This leaves us with 3,854 observations. During this period, we are not able to separate between single-family and multi-family houses. Consequently, it is of special importance to control for the size of the building and location. The final index is constructed in two steps: First, double imputation hedonic indices are calculated separately for six parts of the city.[164] Chaining is used to connect different years. Hedonic regressions use an interaction between lot size and allowed floor space ratio ("*Geschossflächenzahl*") as dependent variable. This

160. Luxurious buildings that sell for a premium.

161. The data structure changes in 2006, such that we have to adapt hedonic regressions.

162. The data classifies eight different types of single-family-houses: semidetached house ("*Doppelhaushaelfte (Einfamilienhaus)*"), detached house ("*Einfamilienhaus (freistehend)*"), row house ("*Reihenhaus (Einfamilienhaus)*"), row-end house ("*Reihenendhaus (Einfamilienhaus)*"), villa ("*Villa*"), individual building style ("*individuelle Bauweise*"), two-family house ("*Zweifamilienhaus*"), and three-family-house ("*Dreifamilienhaus*").

163. The number of missing observations is lower for volume of structure compared to floor area before 2005. Both variables are reasonable proxies for the size of the building.

164. We use the separation described above, but separate the last part again, such that districts ("*Ortsbezirk*") 12 to 15 form the outer north part and district 16 the outer east one. As we are not able to separate between housing types and because different districts typically feature different housing types, the local separation becomes even more important here. Moreover, districts 12 to 15 were only incorporated by Frankfurt in August 1972 and district 16 in January 1977. This implies that the indices for these districts start later (1974 and 1977, respectively). During chaining, we only compare parts of the city for which an index exists for both consecutive years.

interaction term describes a legal ceiling on the total floor space allowed on a developed lot and therefore approximates the size of structure.[165] We do not control for lot area separately.[166] All regressions are performed using maximum likelihood and assuming normally distributed standard errors. Second, a Fisher-type stratification index is build from the part-level indices using chaining and transaction value shares as weights.

To connect the data of 1981 and 1982, we build dummies to categorize the floor space ratio (FSR).[167] To do so, we approximate the FSR for the data in 1982 using actual floor area and lot area.[168] Then, we again calculate indices separately for the five parts of the city also used after 1982. Hedonic regressions use the FSR dummies interacted with lot size. Afterwards, a Fisher-type stratification index is build from the part-level indices using chaining and transaction value shares as weights.

Before 1971, we collected data on all normal sales of residential houses at market prices for most districts of the former city of Frankfurt. We were, however, not able to collect a sufficient number of observations in the west of Frankfurt,[169] such that we had to exclude the western part from our sample. Moreover, we exclude all parts that were not officially part of Frankfurt between 1960 and 1971.[170] We cleaned the data for all buildings, which were (mainly) commercial or public, which were demolished after the transaction, which were used to construct a road or did not have an address. We also exclude all transactions in which only a part of the right to the land or a part of the building was sold ("*ideeller Anteil*"). We drop all observations that have missing prices or that could not be classified as either single-family or multi-family houses.[171] After this procedure, we have 1,525 observations for multi-family houses and 1,235 observations for single-family houses. We again

165. As Frankfurt is a densely populated city, this variable will be highly correlated to actual size of structure. Even in cases when the ceiling was not actually reached, the value of the land will still be highly dependent on the allowed floor space in a dense city.
166. Coefficients for lot area have been very unstable in these regressions. The reason might be that controlling for the size of the structure, lot area and micro-location will be correlated with larger lots typically being in less expensive locations.
167. We build four categories: FSR below 1, FSR between 1 and 2, FSR between 2 and 3 and FSR above 3.
168. This approximation will be downward biased, because to calculate the FSR, a different measure of floor area is used ("*Geschossfläche*" instead of "*Wohnfläche*"). To minimize the effect of the resulting bias, we use the categories instead of controlling for FSR directly. This way, the categories still separate different housing types. Indeed, the resulting index increases considerably less than if using the FSR as control variable directly revealing a considerable downward bias in the approximation of the FSR for 1982. At the same time, it increases noticeably more compared to an index only controlling for lot size, implying that there might have been a large sample shift selling relatively more multi-family houses in 1982. The resulting increase is closer but below the increase found in the real estate market reports data between the two years.
169. District ("*Ortsbezirk*") 6.
170. Districts 12-15.
171. We use the utilization ("*Nutzung*") variable for this classification. This variable is missing for approximately 5% of the sample, which we had to exclude to construct the index.

build a two-step stratification index stratifying by housing type and within types by three parts of the city. As control variables, we only use lot size and for multi-family houses additionally a dummy for whether they have some parts in commercial use.[172] All regressions are performed using maximum likelihood and assuming normally distributed standard errors. To merge 1970 to 1971, we use the same procedure as for the data between 1960 and 1970.[173]

Prior to 1960, we rely on aggregate transaction data for developed lots from various statistical publications.[174] For 1897 to 1934 and 1952 to 1960 we use the average price per square meter of developed lots calculated from the universe of normal sales within the former city of Frankfurt.[175] We link the data from 1934 directly to 1952 using this average price. Unfortunately, as the data are not given disaggregated by district, we have not been able to control for locational shifts within the sample of developed lots. To interpolate the index for the years 1935 to 1938, we had to rely on aggregate transaction data for developed lots, which included normal sales alongside exchanges of land ("*Tausch*") as well as voluntary auctions ("*freiwillige Versteigerung*"). We again use average price per square meter of developed lots, so that we adjust for sample shifts within the size of transacted lots.

Table 1.O.20 summarizes the components of our final house price index.

Rent Series. Considering all data sources we knew of for city-level rent developments, it proved impossible to build a continuous yearly rent index for Frankfurt. To link different rent indices from various sources over time and to minimize the bias resulting from using different sources covering different market segments, we again use data from housing censuses. These data cover the universe of all rented residential dwellings in Frankfurt and enable us to control for size and location within the mix of rented dwellings. It therefore provides a precise picture of city-level rent development. We start by calculating rent increases between the census years 1895, 1905, 1910, 1956, 1968 and 1987. To obtain a yearly rent index, we then use yearly data from the market reports of the *German Real Estate Association* and its predeces-

172. Information on floor area or GFZ is completely missing from the data until 1971.

173. As utilization is missing for a larger part of the sample between 1971 and 1984, we had to exclude a large part of transactions in 1971 to construct the index between 1970 and 1971. As it is not possible to control for the size of the structure in 1970, however, being able to differentiate between single-family and multi-family houses is crucial to control for sample shifts between both years.

174. 1952-1960 and 1938-1939: "*Statistisches Jahrbuch für Frankfurt am Main*" (Volumes 1952 - 1962); 1935-1936: "*Statistisches Jahrbuch deutscher Gemeinden*" (Volumes 1937 - 1938); 1927 - 1934: "*Statistische Jahresübersichten der Stadt Frankfurt a. Main*" (Volumes 1927/28 - 1934/35); 1897 - 1926: "*Statistisches Handbuch der Stadt Frankfurt am Main*" (Volumes 1905/06 and 1929).

175. Data for 1923 to 1925 is missing because of the hyperinflation in Germany.

Table 1.O.20. Final house price index for Frankfurt

PERIOD	SOURCE	DESCRIPTION
1897-1934	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated for former city from yearbooks; *Method*: Average price per square meter of developed land.
1935-1938	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales, exchanges and voluntary auctions aggregated for former city from yearbooks; *Method*: Average price per square meter of developed land.
1952-1960	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated for former city from yearbooks; *Method*: Average price per square meter of developed land.
1960-1982	Own compilation	*Type(s) of dwellings*: Near universe of single-family and multi-family houses; *Type of data*: Transaction-level data from archived records of the Gutachterausschuss Frankfurt; *Method*: Stratified hedonic index.
1982-2018	Own compilation	*Type(s) of dwellings*: Universe of single-family and multi-family houses; *Type of data*: Transaction-level data kindly provided by the Gutachterausschuss Frankfurt; *Method*: Stratified hedonic index.

sor and from *Statistics Frankfurt* to interpolate and extrapolate between and after census years.[176]

The data from housing censuses are taken from various publications by *Statistics Frankfurt*.[177] They cover the universe of all rented residential dwellings within Frankfurt and provide average rents disaggregated by number of rooms, construction period and district. We calculate increases between consecutive census years using stratification indices following Eurostat (2013). Calculating these increases does, however, pose two challenges. First, the way of aggregating and reporting the data changed between census years, such that it is often not straightforward to match the data. Second, the city of Frankfurt grew over time, both by extending its borders spatially and by a high level of new construction. To compare like with like, we exclude buildings constructed between consecutive census years as far as possible. We provide more details in the following paragraph.

176. The housing census in 1987 was the last census in Germany that surveyed rents for the universe of all residential rental dwellings.
177. 1895, 1905, 1910: "*Beiträge zur Statistik der Stadt Frankfurt am Main 11. NF*" (1919); 1956: "*Statistisches Jahrbuch für Frankfurt am Main*" (Volume 1958); 1968: "*Statistisches Jahrbuch für Frankfurt am Main*" (Volume 1971); 1987: "*Frankfurter Statistische Berichte*" ("Sonderheft, Bd. 54").

To calculate the stratification index between 1895, 1905 and 1910, we use data disaggregated by number of rooms (1-6) and subdistrict ("*Stadtbezirk*", number of subdistricts ranging between 48 and 54 depending on the census year).[178] We calculate Laspeyres-type stratification indices using 1910 as baseyear and the total number of rented dwellings by number of rooms and district as weights.[179] Using this stratification, we are able to control for sample shifts in the size of dwellings as well as for fine-grained locations. We are not able to exclude buildings constructed prior to 1910, but as the gap between censuses is not longer than ten years and building periods are highly correlated to locations within cities, we are confident that this does not bias our results. To connect the census data from 1910 and 1956,[180] we use average rent per room disaggregated by subdistrict. To do so, for the 1910 data, we calculate average rent per room for each of the subdistricts ("*Stadtbezirk*", n=50) separately using average rent per dwelling and number of dwellings by subdistrict and number of rooms (1-9). For the 1956 data, we exclude all subdistricts that did not belong to Frankfurt already in 1910 and only use data for dwellings built prior to July 1, 1918.[181] By doing so, we exclude nearly all dwellings built after 1910.[182] With these data at hand, we calculate a Fisher-type stratification index using total number of rooms in rented dwellings per district as weight. The census data in 1968 provide rent per square meter by another classification of subdistricts ("*Ortsteil*", n=38) and building period. We calculate average rent per room from rent per square meter using the average size of dwellings and the average number of rooms per dwelling by subdistrict from the same census year.[183] We aggregate the data from 1956 to the same subdistricts ("*Ortsteil*", n=38) and aggregate all dwellings built prior to 1948. Next, we built a Fisher-type stratification index using rent per rooms of dwellings built prior to 1948. This way, we only compare flats from the same construction period and exclude any new construction. Additionally, we control for any sample shifts in the size or location of dwellings. We calculate the index between 1968 and 1987 using rent per square meter disaggregated by subdistrict ("*Ortsteil*", n=38) and building period. We only use the two building periods prior to 1948 and between 1949 and 1968 for the 1987 census, so we exclude any

178. For each comparison, we match all subdistricts that were part of Frankfurt in both respective years.
179. Data on the number of dwellings by number of rooms and districts are missing for the census years prior to 1910.
180. Data for 1918 and 1950 are missing for Frankfurt. Using 1910 and 1956 we are, however, able to connect rent indices prior to and after World War II accurately.
181. Average rent is only given pooled for all dwellings built prior to 1918, so we are not able to only use dwellings built prior to 1910.
182. Because of World War I, new construction between 1910 and 1918 will have been very low.
183. Source: "*Frankfurter Statistische Berichte*" ("Sonderheft, Bd. 54").

new construction between 1968 and 1987.[184] We calculate the index between both years using Fisher-type stratification by subdistrict and the two building periods. As the total number of square meters by building period and subdistrict is missing, we instead use the total number of dwellings in each stratum as weight. Overall, this procedure arguably gives a reliable picture of rent increases for the rental market in Frankfurt, as we use the universe of all flats excluding new construction and are able to control for size, fine-grained inner-city location and in many cases even building period.

Given these overall increases from the census data, we construct yearly rent indices from various sources to interpolate and extrapolate the long-run index between census years. Starting in 1972, we use the rent data from the market reports of the German Real Estate Association and its predecessor. The construction for rent indices from these market reports is described in the Appendix of the main paper.

For the period from 1949 to 1965 and for 1938, we use monthly rent of a three-room apartment (two rooms plus kitchen) in average distance to the city center built prior to 1924, which was published by Statistics Frankfurt.[185] We link the resulting index with the index for 1968 and the data from the real estate agents' market reports using the census index in 1956, 1968 and 1987. To calculate the rental yield series, we had to linearly interpolate the years 1966, 1967 and 1969 to 1971.

Prior to World War II, we use two different kinds of data from historical publications by Statistics Frankfurt. For the period between 1924 and 1935, we rely on the rent component of the city-level CPI index.[186] The CPI is calculated for less well-off ("*minderbemittelt*") five person households (two adults and three children with age 12, 7 and 1½). The rent component excludes heating and lighting costs. We calculate yearly averages from the monthly data. The index is given in 1914 values, such that the linking to the older data is straightforward. Between 1897 and 1920, we instead use the average rent of dwellings that have been newly rented ("*bezogene Wohnung*") and dwellings for which the rent contract has just ended ("*verlassene Wohnung*") by number of rooms (1-6 or more).[187] We calculate a weighted average rent for each category separately using the number of dwellings by number of rooms from the census in 1910 as weights. Next, we build a simple average over both cat-

184. We aggregate rent per dwelling for dwellings built with and without public financing for the period between 1949 and 1968 from the 1987 census using a weighted average of rent per square meter with number of dwellings by category and district as weights.
185. Source: "*Statistisches Jahrbuch für Frankfurt am Main*" (Volumes 1951 - 1966)
186. Sources: "*Statistisches Handbuch der Stadt Frankfurt am Main*" (1928) and "*Statistische Jahresübersichten der Stadt Frankfurt a. Main*" (Volumes 1927/28 - 1934/35).
187. Source: "*Statistisches Handbuch der Stadt Frankfurt am Main*" (1928).

egories. The resulting index is very close to the index calculated from the housing census data.[188] Data for the period of the hyperinflation in Germany is missing.

Table 1.O.21 summarizes the components of our final rent index. It first depicts the years for which we use the housing census data. Then it describes the components of the yearly rent index. We use the census data to connect the different yearly rent indices. For periods during which both census data and a yearly index exist, we use the yearly indices only to interpolate and extrapolate between and after census years, because we deem the census data to be more reliable.

Table 1.O.21. Final rent index for Frankfurt

PERIOD	SOURCE	DESCRIPTION
1895, 1905, 1910, 1956, 1968, 1987	Own compilation	*Type(s) of dwellings*: All rented residential dwellings; *Type of data*: Census data from statistical publications; *Method*: Stratification - we use these data to link the yearly indices as described in the main text.
1897-1920	Own compilation	*Type(s) of dwellings*: Newly rented and just canceled rented residential dwellings; *Type of data*: Average rent by number of rooms; *Method*: Weighted average.
1924-1935	Statistics Frankfurt	*Type(s) of dwellings*: Apartments for a less-well-off five person household; *Type of data*: From CPI-construction; *Method*: CPI rent index.
1938, 1949-1965	Statistics Frankfurt	*Type(s) of dwellings*: Three-room apartments in average distance to the city center built prior to 1924; *Type of data*: Monthly rent; *Method*: Estimated rent of standardized dwelling.
1972-2018	Own compilation	*Type(s) of dwellings*: Apartments; *Type of data*: New contract rents by construction period and housing quality reported by local real estate agents; *Method*: Matched model approach using mode prices by quality and construction period bins.

Rental Yield Series. Our main benchmark for Frankfurt is taken from *MSCI*, as described in the main paper. This benchmark is very close to all alternative benchmarks we collected for 2018. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.13.

188. Between 1905 and 1910, rents increased in total by 5,96% according to the yearly data and by 5,26% according to the data from the housing censuses. During this period, we still correct for the difference by taking the overall increase from the housing census and impute using the yearly series.

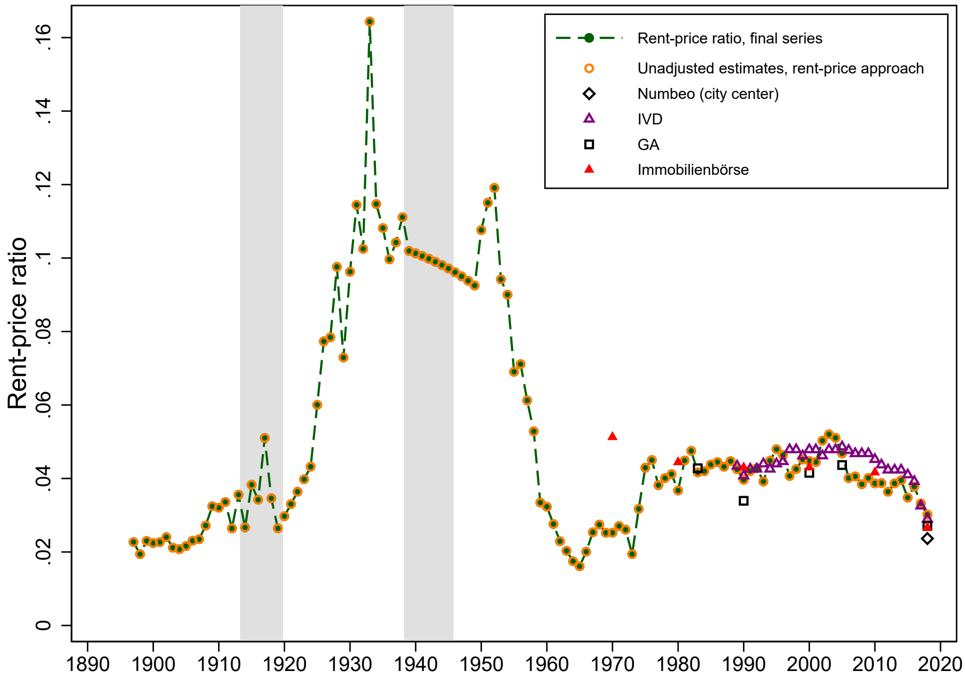

Figure 1.O.13. Frankfurt: plausibility of rental yields

To verify the historical rental yield series, we collected alternative benchmarks from three different sources. First, we use benchmarks from the market reports of the *German Real Estate Association* (IVD). These market reports directly report mode price-rent ratios for residential investment buildings from 1989 onward. The Appendix in the main paper describes how we calculate net rental yields. The resulting rental yield benchmarks are plotted as purple triangles in Figure 1.O.13. This series is very close to our long-run rental yield series.

Second, the transaction-level data provided by the GA Frankfurt contains the yearly gross income for investment buildings between 1982 and 2018. We use these data to calculate mean gross rental yields for these buildings. Following Jordà et al. (2019) we subtract one-third to get net rental yields. We plot benchmarks for the years 2018 (calculated from 76 observations), 2005 (91 observations), 2000 (159 observations), 1990 (157 observations) and 1983 (152 observations).[189] The resulting benchmarks are depicted as black squares in Figure 1.O.13. These benchmarks are also very close to our long-run rental yield series.

189. The number of observations is considerably lower for 1982, hence we instead plot the value for 1983.

Third, we calculate rental yield benchmarks using market reports of the real estate agents association of Frankfurt ("*Frankfurter Immobilienbörse*"). These market reports contain price-rent ratios for investment buildings. The level of detail and accuracy of the reports does, however, increase considerably after 2000. We use these values to calculate net rental yields subtracting one-third for maintenance, depreciation and other costs as done in Jordà et al. (2019). The resulting values for the years 1970, 1980, 1990, 2000, 2010 and 2018 are depicted as red triangles in Figure 1.O.13. The resulting series is very close to our long-run series, except for the value for 1970. We use the 2018 value calculated from these reports as our alternative benchmark in the robustness section of the main paper. This value is nearly indistinguishable from the value calculated using the GA data and close to the value of *Numbeo.com*.

To summarize, all benchmark values we collected are very close to our original rental yield series. The only relevant difference is in 1970, when the benchmark of the reports by the Frankfurt real estate agents association deviates somewhat from our long-run series. The price-rent ratio in this report is, however, only stated as a rough estimate and subject to considerable measurement error. As we use a hedonic house price series built from a high number of observations between 1970 and 2018 and adjust our rent series using housing censuses, we think that the rental yield series calculated using the rent-price approach is more reliable compared to the benchmark in 1970. Therefore, we do not adjust our rental yield series for Frankfurt to any benchmarks.

1.O.6.4 Hamburg

House Price Series. At the time of writing, house price data from the GA Hamburg are not available to us.[190] Instead, we rely on house price data from the market reports of the German Real Estate Association and its predecessor starting in 1972. Prior to 1972, we use data from contemporary publications of Statistics Hamburg throughout. Whenever the data are available by subdivisions of the city of Hamburg, we build stratification indices to control for sample shifts in the location of sold houses. For some years in between, no house price data are available at all. We provide more details below.

In addition to the price data for apartments used in the main paper, the market reports of the German Real Estate Association and its predecessor also provide data on detached and attached single-family houses. To get a broader coverage for the city of Hamburg and to approximate price developments of the entire housing market, and in contrast to the German data set used in the main paper, we use price information for both apartments and single-family houses. We first construct

190. In an upcoming project, we cooperate with the GA Hamburg to digitize their archived house price data and construct hedonic house price series for Hamburg.

a house price index for apartments and for single-family houses separately. The construction of the apartment index is described in the Appendix of the main paper. Single-family houses are separated into two sub-categories: detached single family houses (with a surrounding plot of land and a garage) and attached single-family houses (without a garage).[191] Again, we start with constructing separate indices for both sub-categories. Within these sub-categories, mode prices are given separately for three to four different quality bins. To get a constant quality index, as done for apartments, we use a chained matched-model approach and simple averages over the non-missing quality bins.[192] To construct an overall index for single-family houses, we take a simple average over both sub-categories. Our final house price index for Hamburg between 1972 and 2018 is a simple average of the resulting single-family and apartment indices. This index accurately controls for quality changes over time, as it separates different housing categories and within these categories, is constructed using model dwellings from different quality bins. Quality bins in the original data not only incorporate size and quality of the dwelling itself, but also take the location of the dwelling into account. The main weakness of the index is that it does not adequately reproduce the quality mix within the housing stock in Hamburg, because weights for the different quality bins are missing. To assess the effect of this weakness, we compare house price indices constructed either from the market reports or from transaction-level GA data for Cologne, as for Cologne the GA data are available for both single-family houses and apartments. Figure 1.O.14 plots the results. It shows that the resulting indices for both categories using either the GA data or the market reports are similar. We therefore assume that the bias induced by the missing weights for the quality bins used in the market reports is small.

For the period from 1956 to 1970, we use average prices of developed lots from statistical yearbooks published by Statistics Hamburg.[193] The data covers all sales and voluntary auctions ("*Verkäufe und freiwillige Versteigerungen*") of developed lots within the city of Hamburg. It is given by district ("*Bezirk*") and within districts by two to five subdivisions. We use these subdivisions (22), which are the smallest non-overlapping regional units available, to stratify the data. We build Fisher-type stratification indices using the average sales price of developed lots following Eurostat (2013). This way we are able to control for sample shifts in the location of transacted dwellings. To the extent that housing types and also the size of houses are correlated with location, the fine-grained locational units additionally control for sample shifts along these dimensions. For the years 1955 and 1956, we instead

191. "*Freistehende Eigenheime (inkl. Garage und ortsübl. großem Grundstück)*" and "*Reihenhäuser (Mittelhaus ohne Garage)*".
192. We use a simple average, as data on the distribution of the different bins within the housing stock are not available to us.
193. "*Statistisches Jahrbuch für die freie und Hansestadt Hamburg*" (Volumes 1957-1971).

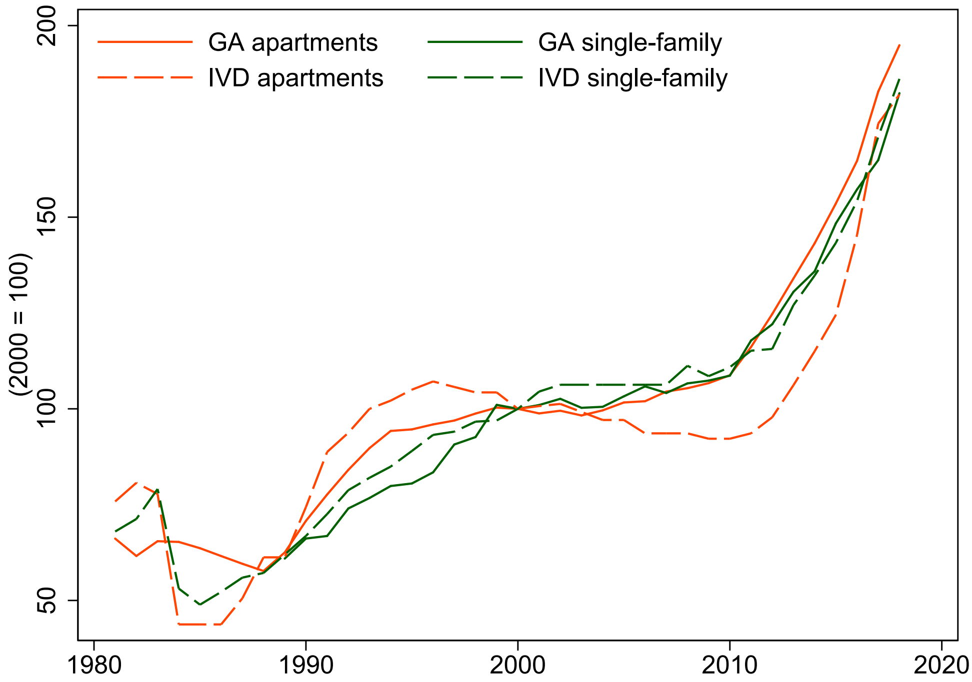

Figure 1.0.14. Nominal house price series from IVD and GA for Cologne, 2000=100

Note: The figure shows house price indices for apartments and single-family houses in Cologne. The IVD indices are constructed from the market reports of the German Real Estate Association and its predecessor as described for Hamburg in the text. The GA indices are stratified hedonic indices from micro-level data provided by the GA Cologne as described in the text about the house price series for Cologne.

had to rely on average transaction prices of developed lots for the entire city of Hamburg from Matti (1963). House price data for 1971 and before 1955 are missing. To match the stratification index to the later data, we use a market report from the predecessor of the German Real Estate Association[194] from the year 1969. We match these data to the data in 1973 using only the middle categories for each detached and attached single-family houses and apartments and averaging over these housing types as described above.[195] We linearly interpolate the house price series for 1971 to calculate housing returns.

194. The "*Ring deutscher Makler*".
195. The data in 1969 are reported in a different format. In these data, quality bins only incorporate the quality of the location. We assume that by taking only the middle quality bin by housing type, mode prices of the different reporting formats are comparable.

Prior to World War II, we again use average prices of all sales of developed lots published by Statistics Hamburg.[196] For the period from 1928 to 1937, the data are provided for different subdivisions of the federal state of Hamburg. We exclude all subdivisions that did not belong to the city of Hamburg during this time period and all aggregates comprised of smaller subdivisions. From the remaining 33 subdivisions, for each pair of consecutive years, we drop all subdivisions that featured less than three sales in one of the two years. Using the remaining subdivisions, we again build Fisher-type stratification indices using the average sales price as described above. To link the data between 1937 and 1956, we match the old subdivisions from 1937 to the new ones from 1956 as accurately as possible. As the city of Hamburg grew considerably in between by incorporating surrounding cities and villages, we exclude the parts of the city in 1956 that did not already belong to the city of Hamburg in 1937.[197] After the matching, we again calculate a Fisher-type stratification index between both years. For the years 1903 to 1928, only average sales prices for developed lots within the entire former city of Hamburg are available.

For the period from 1870 to 1889, Statistics Hamburg reports average sales for publicly sold developed lots.[198] Between 1870 and 1885 the data is given by district ("*Stadtteil*"). We include all districts belonging to the former city ("*Stadt und Vorstadt*") or suburbs ("*Vororte*") of Hamburg (22), but exclude the rural districts around the city of Hamburg that belonged to the federal state ("Landgebiet"). Again we build a Fisher-type stratification index using average transaction price by district. For the years 1885 to 1889, the data is only given by the three categories city, suburbs and rural areas. We again exclude the rural areas and build a Fisher-type stratification index stratifying by the two remaining categories. No house price data is available between 1889 and 1903. We match the data from 1889 to 1903 by comparing average price per transaction for public sales in the former city of Hamburg in 1889 to price per transaction for all sales in the former city of Hamburg in 1903.

196. 1928 - 1937: "*Statistisches Jahrbuch für die freie und Hansestadt Hamburg*" (Volumes 1928-1938); 1903 - 1928: "*Statistisches Handbuch für den Hamburgischen Staat*" (1920) and "*Statistisches Jahrbuch für die freie und Hansestadt Hamburg*" (Volumes 1925-1928).

197. We additionally drop one subdivision of the city of Hamburg in 1956 that only covered a small part already belonging to Hamburg in 1937, but a larger part that did not belong to Hamburg before. As the city is subdivided differently in 1937 and 1956, the matching is not always perfect, so some remaining subdivisions in 1956 additionally cover small parts not belonging to Hamburg in 1937.

198. Developed lots that have been sold at a public exchange market. These encompassed normal sales as well as forced sales (excluding forced sales at the court) and represented approximately 10% of all sales of developed lots. According to Statistics Hamburg, these transactions give a good overview of price movements of all developed lots (see: "*Statistik des Hamburgischen Staats*",Volume 1886, page 176; German definition: "*In der Börse öffentlich verkaufte[..] Grundstücke und zwar sowohl freihändige Verkäufe wie auch die Zwangsverkäufe abseiten des Amtgerichtes Hamburg, desgleich vom Jahre 1883 an die abseiten der Amtsgerichte Bergedorf und Ritzebüttel (umfassend die Landherrenschaften gleichen Names) daselbst öffentlich verkauften Grundtsücke.*"; Source: "*Statistik des Hamburgischen Staats*" (Volumes 1880 & 1886) and "*Statistisches Handbuch für den Hamburgischen Staat*" (1891).

This procedure is potentially biased, because public sales might be a selected sample of all sales. These are, however, no alternative data available that allows for a more precise match.

Table 1.O.22 summarizes the components of our final house price index.

Table 1.O.22. Final house price index for Hamburg

PERIOD	SOURCE	DESCRIPTION
1870-1885	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All public sales aggregated by district from statistical publications; *Method*: Stratification.
1885-1889	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All public sales aggregated by city or suburbs from statistical publications; *Method*: Stratification.
1903-1928	Statistics Hamburg	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales within the former city of Hamburg; *Method*: Average price.
1928-1937	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated by subdivision from statistical publications; *Method*: Stratification.
1955-1956	Matti (1963)	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales and voluntary auctions within the city of Hamburg; *Method*: Average price.
1956-1970	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales and voluntary auctions aggregated by subdivision from statistical publications; *Method*: Stratification.
1972-2018	Own compilation	*Type(s) of dwellings*: Single-family houses and apartments; *Type of data*: Mode prices by housing quality bins reported by local real estate agents; *Method*: Matched model approach using mode prices by housing types and quality bins.

Rent Series. Rent data for Hamburg are taken from various different sources. Starting in 1972, we again rely on the rent data from market reports of the German Real Estate Association and its predecessor. Prior to 1967 and during the interwar period, we use rent indices constructed by Statistics Hamburg during the process of constructing a city-level CPI index. During and prior to World War I, we use average rental data from statistical publications and from Wischermann (1983). No yearly rent data exist for Hamburg between 1967 and 1971. To link the index ending in 1966 to the data starting in 1972 and to get additional data for the year 1968, we use data from housing censuses. We provide more details on the sources and construction of the indices below.

The data collected during the housing censuses are taken from various publications by *Statistics Hamburg*.[199] They cover the universe of all rented residential dwellings within Hamburg and provide average rents disaggregated by construction period and district ("*Bezirk*"). We use housing census data for the years 1956, 1968 and 1987. The data for 1956 contain rents per dwelling additionally disaggregated by number of rooms. For 1968, instead, Statistics Hamburg only published rents per square meter by district and building period, but number of rooms and rents per dwelling are missing. To match the data from different years as precisely as possible, we match the data in both 1956 and 1968 to the data in 1987. These data comprise both rents per dwelling by number of rooms as well as rents per square meter by district and construction period. We calculate an index relative to 1987 for both 1956 and 1968 as described in the next paragraph and infer the price increase between 1956 and 1968 from these two indices. As the city of Hamburg did not grow spatially between 1956 and 1987 and we are able to control for construction period and location, we think that this procedure measures the total rent development in Hamburg very accurately.

To calculate the index between 1956 and 1987, we only use dwellings constructed prior to 1948, such that we are able to exclude all dwellings built after 1956.[200] Still, we are able to stratify the data by two distinct construction periods.[201] Additionally, we stratify the data by district ("*Bezirk*") and number of rooms (2-4).[202] We use rent per dwelling for each stratum to build a Fisher-type stratification index following Eurostat (2013) for the years 1956 and 1987. The index for 1968 and 1987 is calculated using average rent per square meter stratified by district and construction period. Again, we exclude all dwellings built after 1948 and use the same construction period and district bins to calculate a Fisher-type stratification index.

We use the indices from the housing census data to link the yearly index ending in 1966 and the index starting in 1972 and to get an index value for 1968. Starting in 1972, the yearly index uses the rent data from the market reports of the German Real Estate Association and its predecessor. The construction for rent indices from these market reports is described in the Appendix of the main paper. For the period from 1950 to 1966, we use a rent index calculated by Statistics Hamburg collected from statistical yearbooks.[203] This index was calculated to construct a city-level CPI

199. 1956: "*Statistik des Hamburgischen Staats*" (1958); 1968: "*Hamburg in Zahlen*" (1970, "*Sonderheft*" 2); 1987: "*Statistik des Hamburgischen Staats*" (1992).
200. The data for dwellings built between 1948 and 1956 and for dwellings built after 1956 are pooled in the 1987 census.
201. All dwellings built prior to 1918 and dwellings built between 1918 and 1948.
202. We exclude all dwellings with only one room, as this data are missing for 1956, and with more than four rooms, because these data are pooled in the 1987 census. We still cover more than 80% of all dwellings within the relevant construction period bins from the 1987 census.
203. "*Statistisches Jahrbuch für die freie und Hansestadt Hamburg*" (Volumes 1952-1966/67).

index and is intended to track rental costs for a four-person employee household ("*4-Personen-Arbeitnehmer-Haushalt*") with a medium consumption basket ("*Mittlere Verbrauchsgruppe*"). It is given in 1938 values, such that the link to the index used prior to World War II is straightforward. As we were not able to find any rent data for Hamburg for the years 1967, 1969, 1970 and 1971, we linearly interpolate the index for these years to calculate housing returns.

Prior to World War II, we again use a rent index calculated by Statistics Hamburg for CPI construction.[204] It covers the rent of apartments with two rooms and a kitchen and excludes heating and lighting costs. We use yearly averages of the monthly index.[205] For the earlier years, the index is given in 1914 values, so we can directly link the index to the earlier data.

Between 1870 and 1918, average rent for all occupied rented residential dwellings is given in Wischermann (1983) and a publication by *Statistics Hamburg*.[206] We exclude the suburbs ("*Vororte*") only incorporated into Hamburg in 1913 and calculate an index from the average rent for the former city of Hamburg. Between 1875 and 1890, these data are only given in five-year steps and additionally in 1867. We interpolate the missing years by using the average rent for all rented dwellings (residential and commercial, "*Gelasse*") also given in Wischermann (1983).[207] No data are available between 1918 and 1923.

Table 1.O.23 summarizes the components of our final rent index.

Rental Yield Series. The main benchmark for Hamburg is taken from *MSCI*, as described in the main paper. This benchmark is close to the alternative benchmarks we collected for 2018. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.15.

To verify the historical rental yield series, we collected alternative benchmarks from two different sources. First, we use benchmarks from the market reports of the *German Real Estate Association* (IVD). These market reports directly report mode price-rent ratios for residential investment buildings from 1989 onward. The Appendix in the main paper describes how we calculate net rental yields. The resulting rental yield benchmarks are plotted as purple triangles in Figure 1.O.15. This series is above our unadjusted long-run series and decreases faster after 2005, the year with the maximum value after 1990.

204. Source: "*Statistisches Jahrbuch für die freie und Hansestadt Hamburg*" (Volumes 1926/27-1937/38)
205. For 1923, we instead use the end of year value, because only the December value is given in the yearbooks.
206. We use Wischermann (1983) until 1913 and afterwards rent data from "*Statistisches Handbuch für den Hamburgischen Staat*" (1920). The data in Wischermann (1983) is also originally collected from statistical publications.
207. Between 1867 and 1873, we have to rely on linear interpolation instead, because other data are missing.

Table 1.O.23. Final rent index for Hamburg

PERIOD	SOURCE	DESCRIPTION
1956, 1968, 1987	Own compilation	*Type(s) of dwellings*: All rented residential dwellings; *Type of data*: Census data from statistical publications; *Method*: Stratification - we use these data to link the yearly indices as described in the main text.
1870-1913	Wischermann (1983)	*Type(s) of dwellings*: All rented residential dwellings; *Type of data*: Averages from statistical publications interpolated using data for all dwellings between 1870 and 1890; *Method*: Average rent.
1913-1918	Own compilation	*Type(s) of dwellings*: All rented residential dwellings; *Type of data*: Averages from statistical publications; *Method*: Average rent.
1923-1938	Statistics Hamburg	*Type(s) of dwellings*: Apartments with two rooms and a kitchen; *Type of data*: From CPI-construction; *Method*: CPI rent index.
1950-1966	Statistics Hamburg	*Type(s) of dwellings*: Apartments for a four-person employee household; *Type of data*: From CPI-construction; *Method*: CPI rent index.
1972-2018	Own compilation	*Type(s) of dwellings*: Apartments; *Type of data*: New contract rents by construction period and housing quality reported by local real estate agents; *Method*: Matched model approach using mode prices by quality and construction period bins.

Second, in their yearly market reports, the GA Hamburg publishes average price-rent ratios for investment buildings.[208] We use the average values for all buildings for 2005, 2010 and 2018 from the reports. For 1991, 1992 and 2000, we calculate averages for all buildings over construction period and location bins weighted by the number of observations in each bin. Following Jordà et al. (2019) we subtract one-third of the resulting rent-price ratios to get net rental yields. We use the 2018 benchmark as our alternative benchmark in the robustness section of the main paper, because it relies on micro-level data of actual transaction prices from a large number of observations (182). The resulting benchmarks for all mentioned years are depicted as black squares in Figure 1.O.15. These benchmarks are also above our unadjusted series for all years prior to 2018 and depict a larger fall after 2005. As the Hamburg house price series for the last decades, in contrast to the other German cities, is not constructed from micro-level data, but from the real estate agents'

208. "*Verhältnis des Kaufpreises zur Jahresnettokaltmiete*".

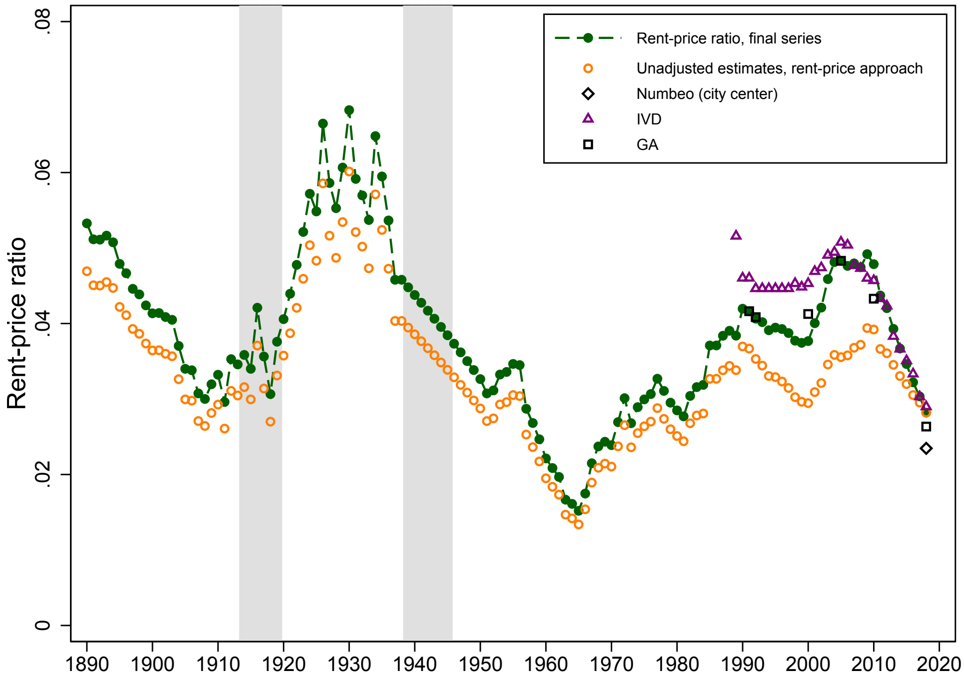

Figure 1.O.15. Hamburg: plausibility of rental yields

market reports, and because the rental yield benchmarks from the two independent sources depict a similar pattern, we believe that these benchmarks are more reliable in comparison to our long-run series. We therefore adjust our long-run series using the GA benchmarks in 2005, the height of the benchmarks after 1990, and in 1991. This gives us the final rental yield series plotted as the green-circled line in Figure 1.O.15. This series is also very close to the GA benchmarks in 2010, 2000 and 1991 and much closer to the IVD series compared to the unadjusted long-run series.

1.O.7 Italy

Italy is a country with a long urban tradition and by 1900 it hosted many large cities. The largest cities were Naples, Milan, Rome and Turin and each had one percent or more of the total population and therefore entered our sample. In absolute terms, Genova, Palermo or Florence also counted large populations of more than 200,000, but failed to meet the 1% threshold. For house prices, we follow the sources of the seminal publication of the Bank of Italy (Cannari, D'Alessio, and Vecchi (2016)) which published a national house price series. We mainly follow its source trail to break numbers down to the regional level. For the early years between 1927 and 1941, *Federazione Fascista dei Costruttori Edili* in principle reports city-level house prices, which however we exclude here because of a data gap for the wartime years. For rents, we largely follow the regional break-down of the national CPI series.

Overall, we think that the quality of the house price series for the Italian cities for the period between 1950 and 1966 is not very high. We were not able to find data to build alternative series, with the exception of Milan. Nevertheless, since the patterns we observe in terms of the price evolution across the Italian cities in our sample and the national series from Knoll, Schularick, and Steger (2017) are very similar, we decided to keep the series in our final data set.

1.O.7.1 Milan

House Price Series. House prices in Milan are taken from a combination of different sources (Table 1.O.24). For the time period 1950 to 1955, we start from the building plot data from Cannari, D'Alessio, and Vecchi (2016). As these exaggerate price movements and ignore building costs, we factor in regional construction costs, taken from Forte and Di Stefano (1970) and Italy's statistical yearbook ("*Anuario Statistico Italiano*"). Following Jordà et al. (2019), we use a construction cost weight of 20 percent. Due to missing regional data, we have to bridge the gap years until 1955 using the national deflator on housing investments from Cannari, D'Alessio, and Vecchi (2016).

We then constructed our own series based on newspaper ads for the period between 1955 and 1966. As the number of ads was insufficient in the early 1950s, we have to start our series in 1955. We use the time dummy hedonic log-linear regression based on newspaper advertisements for flats in Milan taken from *La Notte* and from *Il Corriere della Sera*. We collected a total of 641 ads for the period between 1956 and 1966, which contained information on the price, location and size of the flats. Log prices are regressed on the number of rooms, on a dummy for location for a total of nine neighborhoods in Milan and on dummies for whether the flat has: a bathroom, a kitchen, a heating system, a balcony, a garden, a garage or furniture. Since the two newspapers do not cover the complete period, we first do a regression using the data from both newspapers between 1956 and 1962 and then do a regression using only the ads from *Il Corriere* for the years between 1961 and 1966. Finally, we splice the two indices to build the final index for the years between 1956 and 1966.

From 1966 onward until the current day, we rely on the commercial company *Nomisma's* data from its *Real Estate Market Observatory* which collects data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the newspaper *Sole*. The data allow a break down into new and old housing stock and into different geographic sub-segments (center, semi-center, periphery). Within sub-segments both minimum and maximum price ranges are reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take simple averages of annual square meter prices reported in Euro across all urban market segments. Table 1.O.24 gives an overview of the data used.

Table 1.O.24. Final house price index for Milan

PERIOD	SOURCE	DESCRIPTION
1950-1955	Cannari, D'Alessio, and Vecchi (2016)	*Type(s) of dwellings*: New dwellings; *Type of data*: Official price and cost statistics; *Method*: Weighted indices of all urban centers
1955-1966	Own compilation	*Type(s) of dwellings*: Flats; *Type of data*: Newspaper ads from *La Notte* and *Il Corriere*; *Method*: Time-dummy hedonic index
1966-2018	*Nomisma*	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys; *Method*: Average price of house by quality and geographic housing market segment

Rent Series. Data for rent series are taken from official national statistical sources which report on rent as component of the CPI in regional break downs. We make use of multiple editions of yearbooks to connect the indices reported with varying base years over time. For the early period, we draw on the CPI-series as reported in the city statistical yearbooks and connect it to the indices reported in the national statistical yearbook from 1950 to 1965. The index is based on household surveys on 3-4-room apartments of working-class families in the city.

From 1966 onward, we rely on the commercial company *Nomisma's* data from its *Real Estate Market Observatory* which has been collecting data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the newspaper *Sole*. The data allow a break-down into new and old housing stock and into different geographic sub-segments (center, semi-center, periphery). Within sub-segments both minimum and maximum rent ranges are reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take simple averages of annual square meter rents reported in euros across all urban market segments. Table 1.O.25 gives an overview of the data and methods used.

Table 1.O.25. Final rent index for Milan

PERIOD	SOURCE	DESCRIPTION
1950-1966	*Instituto Centrale di Statistica: Annuario Statistico Italiano*	*Type(s) of dwellings*: 3-4 room working class apartments; *Type of data*: Household survey; *Method*: Index based on CPI-rent component
1966-2018	*Nomisma*	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys ; *Method*: Average rent of house by quality and geographic housing market segment

Rental Yield Series. Our main benchmark for Milan is taken from *MSCI*, as described in the main part of the paper. This benchmark is reasonably close to, but below the alternative benchmarks we collected for 2018 from *Numbeo.com* (which measures city-center yields), to which we subtract one-third costs following Jordà et al. (2019). Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.16. The series shows a rise in rental yields with the gradual lifting of wartime rent controls and a decline ever since 1970, with a short boom in the 1980s. This is the pattern that we find in all Italian cities in our sample. As a result and, since we did not find historical rental yield benchmarks, we decided to keep the unadjusted series as our final rental yield series.

1.O.7.2 Naples

House Price Series. House prices in Naples are taken from a combination of different sources (Table 1.O.26). For the time period 1950 to 1960, we start from the building plot data from Cannari, D'Alessio, and Vecchi (2016). As these exaggerate price movements and ignore building costs, we factor in regional construction costs, taken from Forte and Di Stefano (1970) and Italy's statistical yearbook ("*Anuario Statistico Italiano*"). Following Jordà et al. (2019), we use a construction cost weight of 20 percent. Due to missing regional data, we have to bridge the gap years until 1965 using the national deflator on housing investments from Cannari, D'Alessio, and Vecchi (2016). We have to fall back to this interpolation as we could not identity an accessible newspaper with decent reporting on housing ads as in the case of Milan to build a series of our own.

From 1966 onward until the current day, we rely on the commercial company *Nomisma's* data from its *Real Estate Market Observatory* which has been collecting

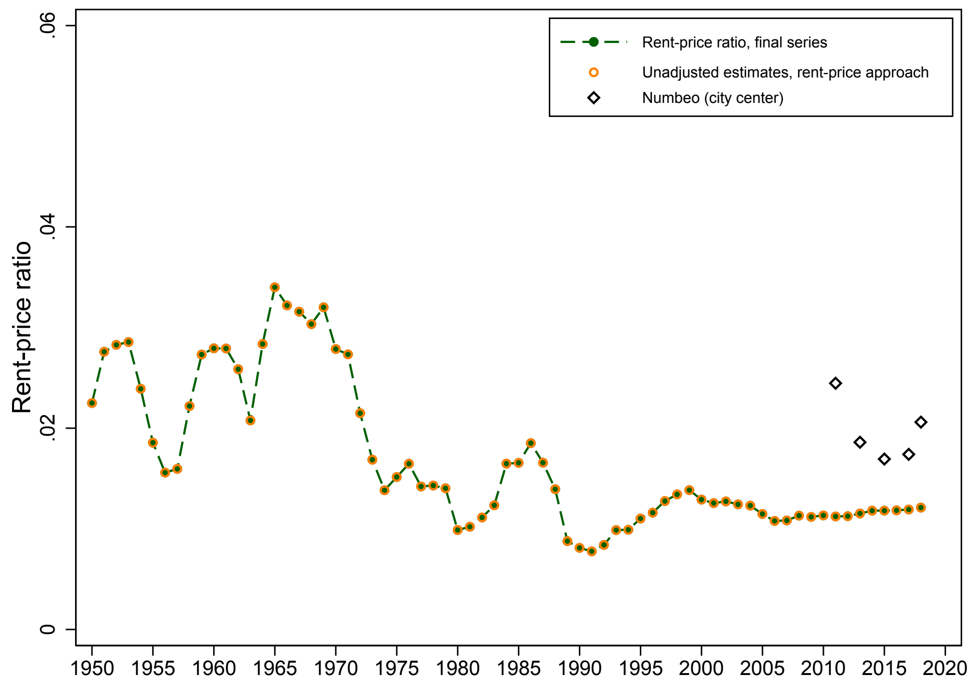

Figure 1.0.16. Milan: plausibility of rental yields

data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the newspaper *Sole*. The data allow a break-down into new and old housing stock and into different geographic sub-segments (center, semi-center, periphery). Within sub-segments both minimum and maximum price ranges are reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take a simple averages of annual square meter prices reported in euros across all urban market segments.

Rent Series. Data for rent series are taken from official national statistical sources which report on rent as component of the CPI in regional break-downs. We make use of multiple editions of yearbooks to connect the indices reported with varying base years over time. For the early period, we draw on the CPI-series as reported in the city statistical yearbooks and connect it to the indices reported in the national statistical yearbook from 1950 to 1965. The index is based on household surveys on 3-4-room apartments of working-class families in the city.

From 1966 onward, we rely on the commercial company *Nomisma's* data from its *Real Estate Market Observatory* which has been collecting data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the

Table 1.O.26. Final house price index for Naples

PERIOD	SOURCE	DESCRIPTION
1950-1960	Cannari, D'Alessio, and Vecchi (2016)	*Type(s) of dwellings*: New dwellings; *Type of data*: Official price and cost statistics ; *Method*: Weighted indices
1960-1966	*Banca d'Italia*	*Type(s) of dwellings*: New dwellings; *Type of data*: Housing investment deflator; *Method*: Index
1966-2018	*Nomisma*	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys; *Method*: Average price of house by quality and geographic housing market segment

newspaper *Sole*. The data allow a break down into new and old housing stock and into different geographic sub-segments (center, semi-center, periphery). Within sub-segments both minimum and maximum rent ranges are reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take a simple averages of annual square meter rents reported in euros across all urban market segments. Table 1.O.27 gives an overview of the data and methods used.

Table 1.O.27. Final rent index for Naples

PERIOD	SOURCE	DESCRIPTION
1950-1966	*Instituto Centrale di Statistica: Annuario Statistico Italiano*	*Type(s) of dwellings*: 3-4-room working class apartments; *Type of data*: Household survey; *Method*: Index based on CPI-rent component
1966-2018	*Nomisma*	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys; *Method*: Average rent of house by quality and geographic housing market segment

Rental Yield Series. Our main benchmark for Naples is taken from *Numbeo.com* for 2018, since *MSCI* does not produce estimates for Naples. Following Jordà et al. (2019) we adjust the estimates for one-third costs. Additionally, we collected benchmarks for recent years also from *Numbeo.com*. The absolute levels of recent yields are relatively low. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.17. The series shows a rise in rental yields with the gradual lifting of wartime rent controls and a decline ever since 1970, with a short boom in the 1980s. This pattern is consistent with what we find for the other Italian cities. As a result and, since we did not find historical rental yield benchmarks, we decided to keep the unadjusted series as our final rental yield series.

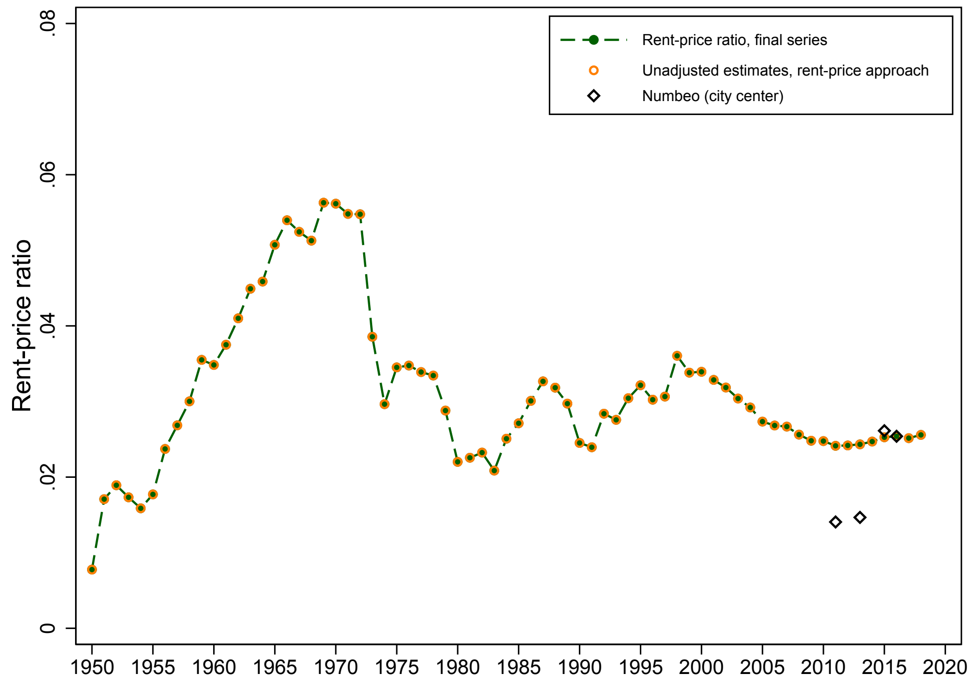

Figure 1.O.17. Naples: plausibility of rental yields

1.O.7.3 Rome

House Price Series. House prices in Rome are taken from a combination of different sources (Table 1.O.28). For the time period 1950 to 1960, we start from the building plot data from Cannari, D'Alessio, and Vecchi (2016). As these exaggerate price movements and ignore building costs, we factor in regional construction costs, taken from Forte and Di Stefano (1970) and Italy's statistical yearbook (*Annuario statistico Italiano*). Following Jordà et al. (2019), we use a construction cost weight of 20 percent. Due to missing regional data, we have to bridge the gap years until 1965 using the national deflator on housing investments from Cannari, D'Alessio, and Vecchi (2016). We have to fall back to this interpolation, as we could not identity an accessible newspaper with decent reporting on housing ads as in the case of Milan to build a series of our own.

From 1966 onward until the current day, we rely on the commercial company Nomisma's data from its *Real Estate Market Observatory* which has been collecting data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the newspaper *Sole*. The data allow a break-down into new and old housing stock and into different geographic sub-segments (Center, semi-center, periphery). Within sub-segments both minimum and maximum price ranges are reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take a simple averages of annual square meter prices reported in euros across all urban market segments.

Table 1.O.28. Final house price index for Rome

PERIOD	SOURCE	DESCRIPTION
1950-1960	Cannari, D'Alessio, and Vecchi (2016)	*Type(s) of dwellings*: New dwellings; *Type of data*: Official price and cost statistics; *Method*: Weighted indices
1960-1966	Banca d'Italia	*Type(s) of dwellings*: New dwellings; *Type of data*: Housing investment deflator; *Method*: Index
1966-2018	Nomisma	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys; *Method*: Average price of house by quality and geographic housing market segment

Rent Series. Data for rent series are taken from official local and national statistical sources which report on rent as a component of the CPI in regional break downs. We make use of multiple editions of yearbooks to connect the indices reported with varying base years over time. For the early period, we draw on the CPI-series as reported in the city statistical yearbooks and connect it to the indices reported in the national statistical yearbook from 1950 to 1965. The index is based on household surveys on 3-4-room apartments of working-class families in the city.

From 1966 onward, we rely on data commercial company *Nomisma's* data from its *Real Estate Market Observatory* which collects data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the newspaper Sole. The data allow a break-down into new and old housing stock and into different geographic sub-segments (center, semi-center, periphery). Within sub-segments both minimum and maximum rent ranges are reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take simple averages of annual square meter rents reported in euros across all urban market segments.

Rental Yield Series. Our main benchmark for Rome is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to the alternative

Table 1.O.29. Final rent index for Rome

PERIOD	SOURCE	DESCRIPTION
1950-1951	*Annuario Statistico di Roma*	*Type(s) of dwellings*: 3-4-room working class apartments; *Type of data*: Household survey; *Method*: Index based on CPI-rent component
1951-1966	*Instituto Centrale di Statistica: Annuario Statistico Italiano*	*Type(s) of dwellings*: 3-4-room working class apartments; *Type of data*: Household survey; *Method*: Index based on CPI-rent component
1966-2018	*Nomisma*	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys; *Method*: Average rent of house by quality and geographic housing market segment

benchmark we collected for 2018 from *Numbeo.com* (which measure city center yields), for which we assume one-third costs as in Jordà et al. (2019). Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.18. The series shows a rise in rental yields with the gradual lifting of wartime rent controls and a decline ever since 1970, with a short boom in the 1980s. Again, this is the same pattern as in the other Italian cities, although in the case of Rome it seems to be less pronounced. As a result and, since we did not find historical rental yield benchmarks, we decided to keep the unadjusted series as our final rental yield series.

1.O.7.4 Turin

House Price Series. House prices in Turin are taken from a combination of different sources (Table 1.O.30). Lacking city-specific sources as used in the cases of other Italian cities, we have to fall back on the big-city average taken from Cannari, D'Alessio, and Vecchi (2016), as we could not identity an accessible newspaper with decent reporting on housing ads as in the case of Milan to build a series of our own.

From 1966 onward until the current day, we rely on the commercial company *Nomisma's* data from its Real Estate Market Observatory which has been collecting data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the newspaper *Sole*. The data allow a break down into new and old housing stock and into different geographic sub-segments (center, semi-center, periphery). Within sub-segments both minimum and maximum price ranges are

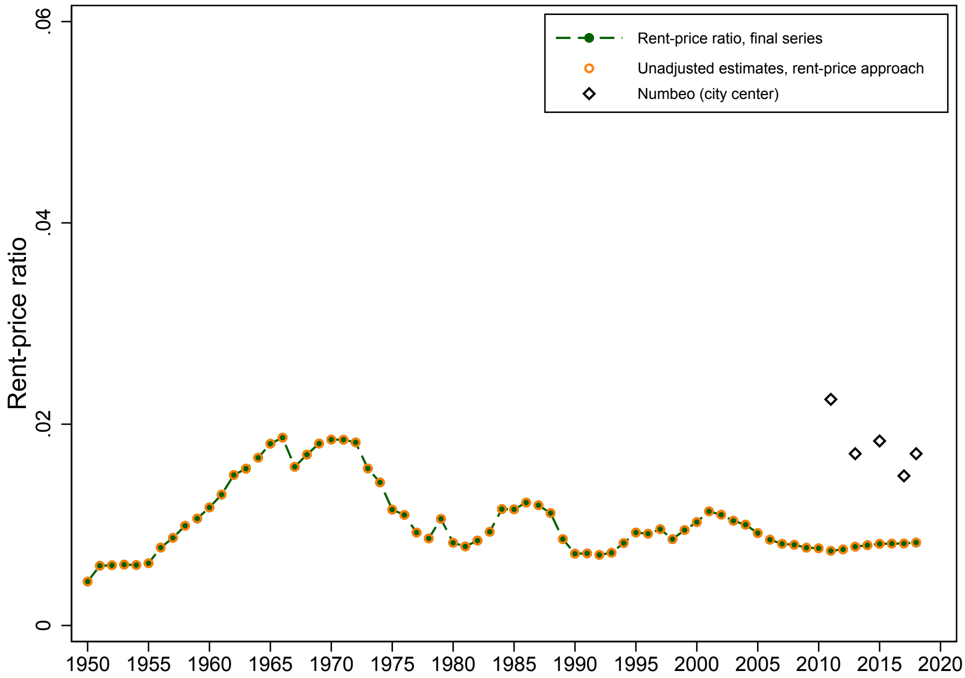

Figure 1.O.18. Rome: plausibility of rental yields

reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take simple averages of annual square meter prices reported in euros across all urban market segments.

Table 1.O.30. Final house price index for Turin

PERIOD	SOURCE	DESCRIPTION
1950-1966	Cannari, D'Alessio, and Vecchi (2016)	*Type(s) of dwellings*: New dwellings; *Type of data*: Official price and cost statistics ; *Method*: Weighted indices of all urban centers
1966-2018	Nomisma	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys; *Method*: Average price of house by quality and geographic housing market segment

Rent Series. Data for rent series are taken from official national statistical sources which report on rent as a component of the CPI in regional break downs. We make use of multiple editions of the national yearbooks ("*Annuario Statistico Italiano*") to connect the indices reported with varying base years over time. We use these data to build an index from 1950 to 1965. The index is based on household surveys on 3-4-room apartments of working-class families in the city.

From 1966 onward, we rely on the commercial company *Nomisma's* data from its *Real Estate Market Observatory* which collects data on different segments of the residential real estate market itself since 1988. For the period 1966 to 1987, it relied on pre-existing data mainly from *Consulente Immobiliare* and the newspaper *Sole*. The data allow a break-down into new and old housing stock and into different geographic sub-segments (center, semi-center, periphery). Within sub-segments both minimum and maximum rent ranges are reported. As there are no data on the prevalence of these segments in the overall urban housing stock, we take simple averages of annual square meter rents reported in euros across all urban market segments. Table 1.O.31 gives an overview of the data and methods used.

Table 1.O.31. Rents in Turin

PERIOD	SOURCE	DESCRIPTION
1950-1966	*Instituto Centrale di Statistica: Annuario Statistico Italiano*	*Type(s) of dwellings*: 3-4-room working class apartments ; *Type of data*: Household survey; *Method*: Index based on CPI-rent component
1966-2018	*Nomisma*	*Type(s) of dwellings*: Old and new dwellings; *Type of data*: Commercial market surveys; *Method*: Average rent of house by quality and geographic housing market segment

Rental Yield Series. Our main benchmark for Turin is taken from *Numbeo.com*, as *MSCI* does not provide estimates for Turin. Following Jordà et al. (2019) we assume one-third costs to have an estimate of the net yield. This benchmark is reasonably close to the alternative benchmarks we collected for 2018 from the *Deloitte Property Index*. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in in Figure 1.O.19. The series shows a rise in rental yields with the gradual lifting of wartime rent controls and a decline ever since 1970, with a short boom in the 1980s. This is the same pattern we find for the other cities. As a result and, since we did not find historical rental yield benchmarks, we decided to keep the unadjusted series as our final rental yield series.

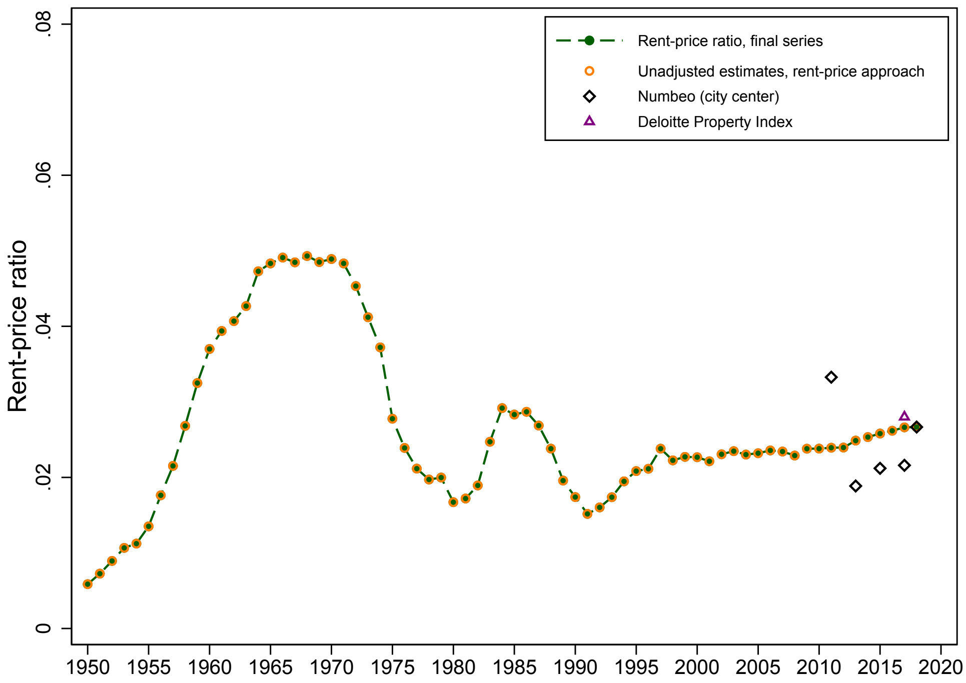

Figure 1.O.19. Turin: plausibility of rental yields

1.0.8 Japan

In 1900 the largest four cities in Japan were in descending order: Tokyo, Osaka, Kyoto and Nagoya. Of these four cities, only Tokyo and Osaka represented more than 1% of the national population in 1900. Tokyo was by far the largest city in Japan with more than two times the population of Osaka and represented around 3.5% of the national population.

To the best of our knowledge there do not exist regional quality-adjusted house price series for Japan for the pre-1975 period.[209] LaPoint (2020) has assembled a very extensive data set containing house price indices for 300 different cities in Japan for the period between 1975 and 2015. Unfortunately, rent data and housing return data are missing for most of these cities; sufficient rent data is only available for Tokyo. Additionally, there has been very exhaustive work on the evolution of prices in Tokyo around the housing bubble at the end of the 1980s.[210] Hence, we only include Tokyo in our long-run data set.

As we explain in more detail below, our main contribution to the history of housing market developments in Japan is the construction of a brand-new hedonic house price index for the period between 1950 and 1975.

1.0.8.1 Tokyo

House Price Series. Shimizu and Nishimura (2007) built a hedonic land price index for the Setagaya Ward in Tokyo for the period between 1975 and 1999. The authors collected a total of 7,991 residential land transaction prices in the Setagaya Ward, which is a famous and expensive residential neighborhood in Tokyo, from the local land registry offices. They used these data to build a time dummy hedonic index, in which they regressed the log price of land on the following set of controls: land lot size, width of road frontage, distance to nearest station, time to Central Business District, floor-to-lot ratio and a railway dummy factor.

Hill et al. (2018) built a hedonic house price index for the city of Tokyo for the period between 1986 and 2016 using asking prices of apartments collected from the *Residential Information Weekly* (*Shukan Jyutako Joho*). In total the authors use 237,190 observations, which are spread around the 23 special wards of the prefecture of Tokyo. The index is a rolling time dummy index with a four-quarter rolling window which controls for the following variables: log of floor area, age, time to nearest station, time to Tokyo Central Station and a ward dummy.

LaPoint (2020) built a residential price index for Tokyo from 1975 to 2015 using appraisals data from official real estate appraisers. The author built an extensive

209. Bank of Japan (1986) published house price indices for the six largest metropolitan areas in Japan for the periods 1913-1930 and 1936-1965, based on average residential land appraised values, i.e. without any quality adjustments.
210. See for example the work by Shimizu, Nishimura, and Watanabe (2016)

data set containing almost the universe of land plot appraisals in Japan since 1975. A land plot appraisal takes into account not only the land, but also the building on top of it. Using residential land plots, which are appraised on a yearly basis, the author builds a "repeat appraisal" index in which he regresses the log appraisal value on a time dummy and a land plot fixed effect, which controls for all time-invariant observed and unobserved characteristics of the land or buildings existing on the plot. One concern with this series is the fact that it is based on appraisals and not on actual transaction prices. However, the author shows that the repeat appraisal indices he built correlate very strongly with actual repeat sales indices for overlapping periods.

The Japan Real Estate Institute (JREI) publishes a house price index for Tokyo based on existing apartment sales in the 23 special wards of Tokyo on a monthly basis since 1993. The so-called Fudoken Housing Price Index for the prefecture of Tokyo is based on transaction prices of existing apartments from the official database of real estate registry in Japan, the Real Estate Information Network System (REINS) (Institute, 2021).[211] The index is a weighted least squares repeat sales index.

Since there were no quality-adjusted price series available for the period pre-1975, we built a hedonic price index based on newspaper asking prices. We collected a total of 3,766 observations on single-family houses for the period between 1950 and 1975 from the real estate ad section of the newspaper *Yomiuri*.[212] We built a rolling time dummy index with a five-year rolling window in which we regress the log asking price on the log square meters of the house and dummy, which divides the city into an expensive and a cheap part. To do so, we follow the classification from Diewert and Shimizu (2015) and define the wards 1-4, 7-11 and 13-14 as the expensive part of Tokyo, and the wards 5-6, 12 and 15-21 as the cheap part of the city.

Table 1.O.32 summarizes the components of our final house price index. For the period between 1950 and 1975 we use our own index, since it is the only quality-adjusted house price index for the pre-1975 period. From 1975 to 1986 we rely on the repeat-appraisals index from LaPoint (2020), since it covers the whole city of Tokyo and not only the Setagaya ward. From 1986 to 1993 we opted to use the index by Hill et al. (2018), which is based on a very extensive and representative set of asking prices. This is the period of the famous housing boom in Japan, which peaked in 1989. Shimizu, Nishimura, and Watanabe (2016) make an extensive comparison of repeat sales and hedonic indices around this period and find that the turning points in the repeat-sales indices usually lag behind the ones in the hedonic

211. Newly constructed apartments are not considered for the index.
212. We are very grateful to Masashi Tanigaki, without whom we would not have been able to build this index.

indices.[213] As such, we chose to use the index by Hill et al. (2018) instead of the index by LaPoint (2020) for this period. For post-1993 we can rely on the official index from JREI, which is based on the universe of transaction prices in Tokyo.

Table 1.O.32. Final house price index for Tokyo

PERIOD	SOURCE	DESCRIPTION
1950-1975	Own compilation	*Type(s) of dwellings*: Single-family houses; *Type of data*: Asking prices from the newspaper *Yomiuri*; *Method*: Five-year rolling window hedonic index.
1975-1986	LaPoint (2020)	*Type(s) of dwellings*: Residential land plots; *Type of data*: Appraisals from official real estate appraisers; *Method*: Repeat appraisal index.
1986-1993	Hill et al. (2018)	*Type(s) of dwellings*: Apartments; *Type of data*: Asking prices from the *Residential Information Weekly*; *Method*: Four-quarter rolling-window hedonic index.
1993-2018	Institute (2021)	*Type(s) of dwellings*: Existing apartments; *Type of data*: Transaction prices from the Real Estate Information Network System data set; *Method*: Weighted least squares repeat sales index.

Rent Series. The *Tokyo Statistical Yearbook* has published a yearly rent index for Tokyo since 1947, which is used to build the official CPI series for Tokyo. The index is based on data from the survey on family consumption and expenditures, which is conducted by the *Statistics Bureau of Japan*. The index is based on a matched-model approach, according to which the rent price change over time is calculated based on rents for the same dwellings.[214] Since the classification of rent indices changed over time in the *Tokyo Statistical Yearbook*, we had to splice different series. From 1950 to 1970, we use the index on house and land rent and from 1971 onward we rely on the rent index. As an alternative, we could have used a housing index, which also includes imputed rents. However, in order to be consistent with the national rent index for Japan from Jordà et al. (2019), we chose to use the pure rent index. Also, to make the Tokyo rent series comparable to the national rent index from Jordà et al. (2019), we make the assumption that the rent series understated the growth in rents by a factor of 2 between 1960 and 1969 as well.

Table 1.O.33 summarizes the components of our final rent index. To the best of our knowledge the rent index by the Statistics Bureau of Japan is the only existing

213. They attribute these differences to the non-randomness in the repeat sales sample.
214. Shimizu, Nishimura, and Watanabe (2010) give a good overview of the methodology employed by the *Statistics Bureau of Japan*.

long-run quality-adjusted index for Tokyo. As such we use it for the complete period between 1950 and 2018.

Table 1.O.33. Final rent index for Tokyo

PERIOD	SOURCE	DESCRIPTION
1950-2018	*Tokyo Statistical Yearbook* (various years)	*Type(s) of dwellings*: Renter-occupied dwellings; *Type of data*: Rent prices from the survey on family consumption and expenditures; *Method*: Matched-model index.

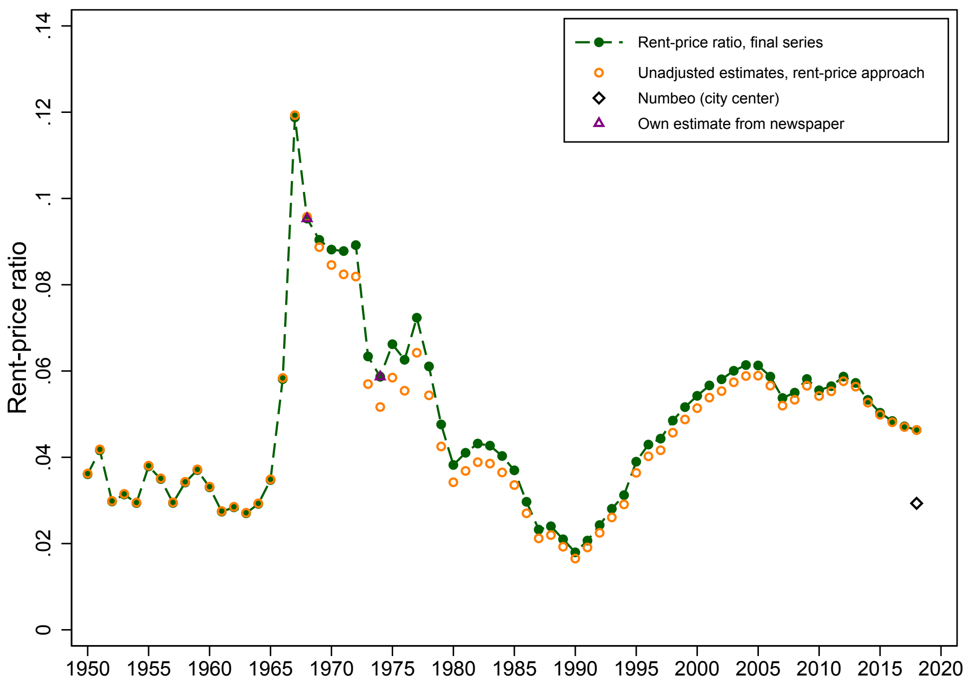

Figure 1.O.20. Tokyo: plausibility of rental yields

Rental Yield Series. Our main benchmark for Tokyo is taken from *MSCI*, as described in the main paper. This benchmark is slightly above the benchmark we collected for 2018 from *Numbeo.com*. According to *Numbeo.com* the gross rental yield in the city center of Tokyo was 4.4% in 2018; adjusting for one-third costs we estimate a net rental yield of 2.9% for 2018. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.20.

Additionally, we collected rental yield benchmarks from the newspaper *Yomiuri* using real estate ads which contained both asking price and gross rental income for the same apartment. In total we collected 110 observations for the years 1968 and 1974 for apartments in the city of Tokyo. For both years we use the average rental yield as benchmark.[215] For 1968 we estimate a gross rental yield of 14.3% and for 1974 8.8%. We then adjust the gross yields for one-third costs, which results in the net yield estimate in Figure 1.O.20. Since due to the high number of observations we think that these estimates are a good approximation of the actual yields in Tokyo at the time, we use them to benchmark our final yield series. This gives us the adjusted final rental yield series—the green-circled line in Figure 1.O.20.

215. The median rental yield conveyed very similar results.

1.O.9 Netherlands

In 1900 the three largest cities in the Netherlands were in descending order: Amsterdam, Rotterdam and The Hague. All of these cities represented more than 1% of the total national population in 1900.[216] There exist very good series on Amsterdam, not only for prices and rents, but also for housing returns, which we explain in more detail below. To the best of our knowledge there do not exist historical house price or rent series for the other Dutch cities. Since Amsterdam alone represented 10% of the total population, we did not build indices for the other cities.

1.O.9.1 Amsterdam

House Price Series. Francke and Korevaar (2019) constructed a long-run house price index for Amsterdam for the period between 1625 and 2017. The authors combined different repeat-sales data sets in Amsterdam to build a long-run repeat-sale house price index. For the period of analysis in this paper (1870-2018), the authors use three different data sets to build the final index. From 1870 to 1975 they combined the repeat-sales data set from Eichholtz (1997), which contains 5,269 repeat sales of houses on the Herengracht canal in Amsterdam, with a data set from Verwey (1943), who collected 2,880 repeat sales of properties in central Amsterdam auctioned between 1840 and 1940. For the period after 1975, the authors use 13,720 repeat sales for the city of Amsterdam from the data set of the Dutch Association of Realtors (NVM). To deal with the low number of observations in certain periods the authors employ the repeat-sales method developed in Francke (2010), which includes a local linear trend model, thereby reducing the noise in the periods with fewer transactions.

We updated the long-run index by Francke and Korevaar (2019) to 2018 using the house price index for Amsterdam constructed by *Statistics Netherlands* (CBS) using the sale price appraisal ratio (SPAR) method and data from the Dutch land registry office. More details about the construction of the series can be found in De Vries et al. (2009).

Table 1.O.34 summarizes the components of our final house price index. We decided to use the index by Francke and Korevaar (2019) and not the long-run repeat-sales index by Eichholtz (1997), which covers the period between 1628 and 1973, for two reasons. Firstly, the index by Francke and Korevaar (2019) includes significantly more observations, due to the inclusion of the data from Verwey (1943). Secondly, because the index by Eichholtz (1997) only focuses on houses along the Herengracht canal, which is famous for being one of the most expensive in Amsterdam, it might be not representative of the entire city.

216. Reba, Reitsma, and Seto, 2016.

Table 1.O.34. Final house price index for Amsterdam

PERIOD	SOURCE	DESCRIPTION
1870-2017	Francke and Korevaar (2019)	*Type(s) of dwellings*: Owner-occupied dwellings; *Type of data*: Transaction and auction data; *Method*: Repeat-sales.
2017-2018	Netherlands (2020)	*Type(s) of dwellings*: Owner-occupied dwellings; *Type of data*: Transaction data; *Method*: SPAR method.

Rent Series. Eichholtz, Korevaar, and Lindenthal (2019) built a long-run rent index for Amsterdam for the period between 1550 and 2018. For the time period considered in this paper (1870-2018) their index is constructed based on data from different sources. For the period between 1870 and 1940 the authors collected rent prices from rental contracts in the Amsterdam City Archives. The largest share of rental contracts comes from the archives of the *Burgerweeshuis* (the Amsterdam orphanage) but also from the archives of the *Brants-Rus Almshouse* (the Roman-Catholic orphanage), and from the archives of different churches in Amsterdam. The authors use a repeat-rent approach based on the method developed in Francke (2010) to build the rent index from 1870 to 1940. For the period after 1940, the authors use the rent price index of the *Amsterdam Statistical Office*, which according to the authors follows the standards of *Statistics Netherlands*. Between 1994 and 2000, the authors rely on the rent component of the national rental index by *Statistics Netherlands*, which is built based on a sample of around 15,000 Dutch households. For the period after 2000 the authors use the index on average rent per square meter in Amsterdam constructed by Dröes, Houben, Van Lamoen, et al. (2017).

The rent series since 1940 mostly do not adjust for quality changes; however, as argued in Eichholtz, Korevaar, and Lindenthal (2019), this period was marked by very strict rent controls in the Netherlands, which were especially strong in Amsterdam. These rent controls were in place from 1927 until the late 1970s. Eichholtz, Korevaar, and Lindenthal (2019) argue that the rent series in that period are, thus, a good approximation of actual market rent growth.

Table 1.O.35 summarizes the components of our final rent index. To the best of our knowledge there do not exist any alternative rent indices for Amsterdam that we could use. As a result, we simply rely on the index by Eichholtz, Korevaar, and Lindenthal (2019).

Rental Yield Series. Our main benchmark for Amsterdam is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to the alternative benchmark we collected for 2018 from *Numbeo.com*. According to *Numbeo.com* the gross residential rental yield in the city center of Amsterdam in 2018 was 5.12%, to which we discount one-third costs, which gives us a net yield estimate of 3.41%.

Table 1.O.35. Final rent index for Amsterdam

PERIOD	SOURCE	DESCRIPTION
1870-2018	Eichholtz, Korevaar, and Lindenthal (2019)	*Type(s) of dwellings*: Renter-occupied dwellings; *Type of data*: Rent prices from rental contracts; *Method*: Repeat-rent and average rent per square meter.

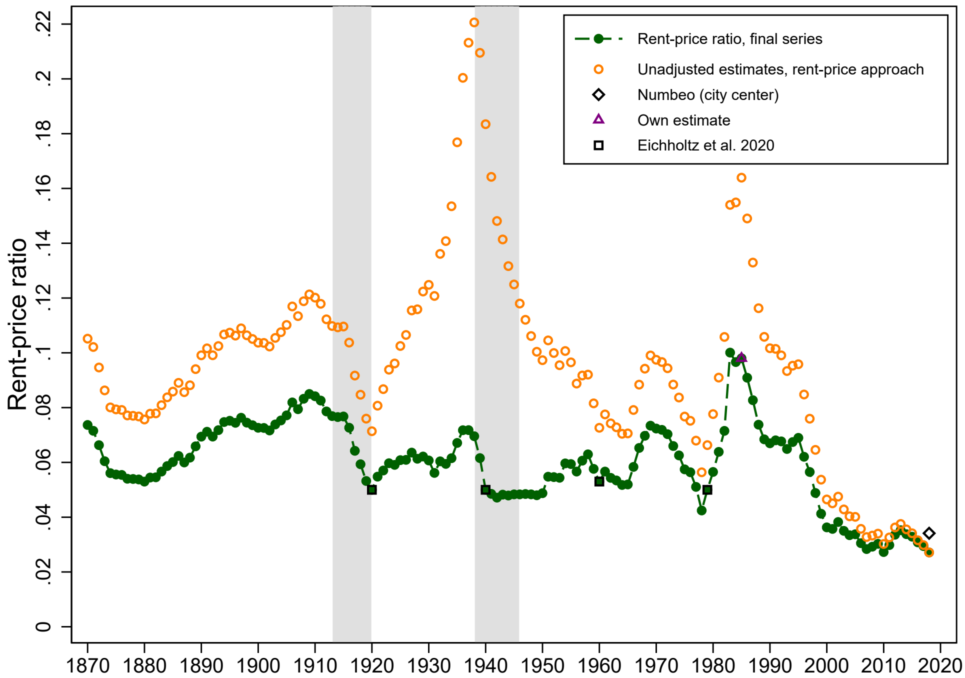

Figure 1.O.21. Amsterdam: plausibility of rental yields

Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.21.

As is visible from Figure 1.O.21 the unadjusted series rises substantially in the 1980s and in the interwar period. As mentioned above, rent controls were introduced in Amsterdam in 1927 and were slowly lifted after World War II until the end of the 1970s. One concern might be that the house price series over-samples a segment of the housing market, which was not under the rent control, while the rent series is based on a segment of the housing market strongly affected by the rent controls. This could create a strong upward bias in our rental yield series for this period, since our price series grows substantially more than the rent series.

To check whether this is actually the case we collected rental yield benchmarks from two different sources. For the years 1920, 1940, 1960 and 1979 we rely upon the estimates from Eichholtz et al. (2020), who built a net rental-yield series for Amsterdam using price and rental data for the same properties from the registers of a local real estate agents company. Since the authors have access to the exact rent amount received by each property and the associated costs, they are able to calculate very accurate net rental yields. As is clear from Figure 1.O.21 our unadjusted series lies significantly above these benchmarks. As a result, we use the benchmarks to adjust our series.

Since the series by Eichholtz et al. (2020) stops in 1979, we collected rental yield estimates for the year 1985 from the newspapers *De Telegraaf* and *Het Parool*. In total we collected 35 observations which feature both asking price and gross rental income for houses situated in Amsterdam.[217] The average gross-yield estimate is 18.8%. We then apply the same cost estimates from Eichholtz et al. (2020) for the year 1979 to get a net yield estimate of 9.8%. According to Eichholtz et al. (2020) taxes represented 17.6% and other costs 28% of the purchasing price. As far as we know there were no major changes to property taxes in the 1980s in Amsterdam. Additionally, we also adjust for vacancies, which were around 2% in Amsterdam in that period.[218] Again our benchmark lies substantially below the unadjusted rental yield series, as is clear from Figure 1.O.21. As a result, we also adjust our final series to the benchmark in 1985. This gives us the adjusted final rental yield series—the green-circled line in Figure 1.O.21.

217. Originally, we had collected 60 observations. We had to discard 25 of these, since it was not clear whether the rental income reported on the ad was for the whole house or only for a part of it. This was commonly the case when the house had a commercial store on the ground floor and residential apartments in the upper floors.
218. Eichholtz et al., 2020.

1.O.10 Norway

Oslo was clearly the largest city in Norway, counting 227,000 inhabitants or a bit more than ten percent of the total population in 1900. It has also been covered in a project of the central bank with high-quality long-run house price data (Eitrheim and Erlandsen (2004)). This project also covered the three smaller cities of Bergen, Trondheim and Kristiansand, for which, however, there are no rental data, whereas there is some existing research on Oslo's rental market we can draw on (Oust, 2013). These cities also had only one third or less of Oslo's population in 1900.

1.O.10.1 Oslo

House Price Series. The house price index in Oslo is taken from the Norges Bank (Eitrheim and Erlandsen, 2004) and is built using a repeat sales method based on transaction data on different types of dwellings between 1870 and 1985 (cf. 1.O.36). For the time period between 1985 and 2009, the data come from the Norwegian association of real estate agents (*Norges Eiendomsmeglerforbund*) on the basis of which Norges Bank publishes a hedonic price index of detached and semi-detached houses. Since 2009, we draw on the hedonic index of existing detached houses, row houses and multi-family houses by *Statistics Norway* for Oslo and Bærum based on data from *Finn.no*. *Finn.no* is a website which advertises residential properties, but also collects data on actual sales from the largest and most important real estate companies in Norway. We deciced to use this series since 2009, because our rent series for the same period also covers Oslo and Bærum.

Rent Series. The rent index combines different sources (1.O.37). First, for the period 1892-1950, we draw on the city yearbooks, which contain information on absolute rent levels for flats of different sizes and quality for benchmark years, but also a CPI-index for Oslo including a separate rent component which we extracted.

For the time period between 1950 and 1970, we adopted the data source and methodology from Oust (2013) by extracting about 260 annual rent price offers from the local newspaper *Aftenposten* and estimating a time-dummy hedonic regression of the log rent levels on year dummies, controlling for the number of rooms, the geography and the market segment. As market segments, the rental market was composed of two segments: the offers for exchanging rental units and rental market offers (similar as in Gothenburg). As geography, we recoded the addresses and districts from the ads into center, south, west, east, and north, following Oust (2013) on whose index we draw for the period between 1971 and 2008.

Since 2009, we use the rental market survey from Statistics Norway and the average annual rents for three-room apartments in the Oslo and Bærum municipalities.

Table 1.O.36. Final house price index for Oslo

PERIOD	SOURCE	DESCRIPTION
1870-1985	Eitrheim and Erlandsen (2004) as reported by Norges Bank	*Type(s) of dwellings*: Owner-occupied residential dwellings; *Type of data*: Transaction data from official real property registers; *Method*: Repeat sales
1985-2009	Eitrheim and Erlandsen (2004) as reported by Norges Bank	*Type(s) of dwellings*: Detached and semi-detached houses; *Type of data*: Transaction data from association of real estate agents; *Method*: Hedonic price index
2009-2018	Statistics Norway as reported by Norges Bank	*Type(s) of dwellings*: Different types of existing dwellings; *Type of data*: Transaction data on existing residential dwellings from proivded by *Finn.no*; *Method*: Hedonic price index

Table 1.O.37. Final rent index for Oslo

PERIOD	SOURCE	DESCRIPTION
1892-1950	Yearbook of the city of Oslo (various years)	*Type(s) of dwellings*: Flats; *Type of data*: Municipal cost of living survey; *Method*: Rent component of the cpi series for Oslo
1950-1970	Own compilation	*Type(s) of dwellings*: Flats; *Type of data*: Newspaper ads from *Aftenposten*; *Method*: Stratified adjacent period time dummy hedonic rent index
1970-2008	Oust (2013)	*Type(s) of dwellings*: Flats; *Type of data*: Newspaper ads from *Aftenposten*; *Method*: Hedonic rent index
2008-2019	Statistics Norway	*Type(s) of dwellings*: three-room flats; *Type of data*: Rental market survey; *Method*: Simple average

Rental Yield Series. Our main benchmark for Oslo is *Numbeo.com*, as *MSCI* data are not available. The benchmark is for Oslo's city center and reasonably close to the alternative benchmark collected from *Catella* reports.[219] The latter lies slightly above our curve, as it reports on prime real estate only. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.22, which largely follows the trend

219. Source: Catella, "European commercial residential market map 2018".

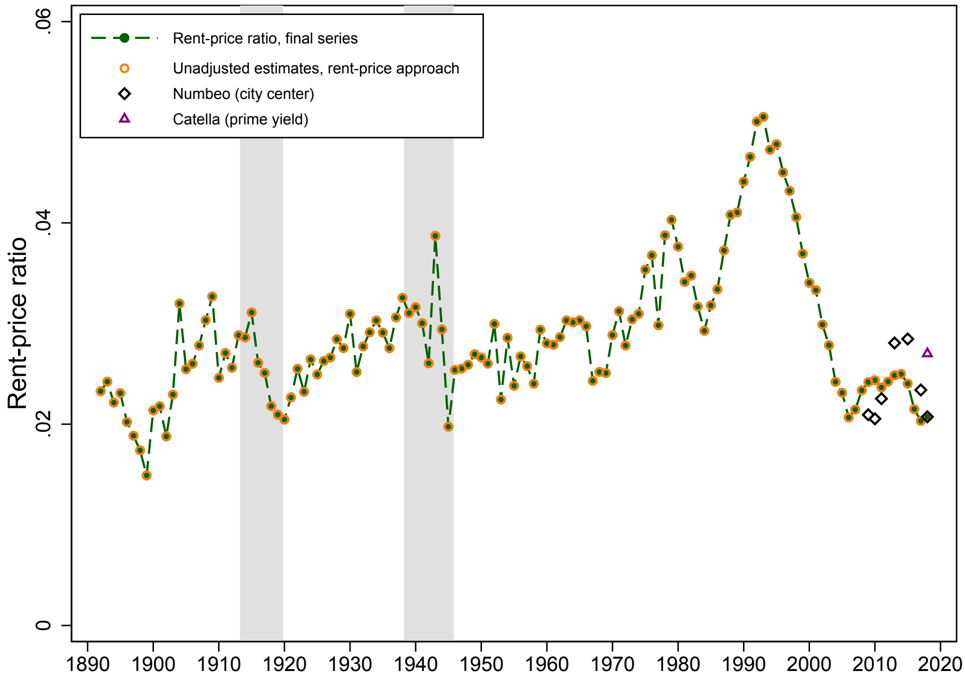

Figure 1.O.22. Oslo: plausibility of rental yields

in the national return series from Jordà et al. (2019). The series shows how the war-related rent control led twice to declines in rental yields with long post-war recoveries, the latter of which built up towards the 1990 Scandinavian house price burst, which was followed by a steep decline in rental yields. Given the high quality of the house price and rent series and the fact that we could not find historical rental yield benchmarks, we decided to keep the unadjusted series as our final series.

1.0.11 Spain

In 1900 the three largest cities in Spain were in descending order: Barcelona, Madrid and Valencia. Each of the cities represented more than 1% of the total national population. Barcelona and Madrid were by far the largest and together represented 6% of the population.

Since 2007, the *Spanish Institute of Statistics* (INE) has been publishing high-quality house price series for different Spanish regions, which we explain in more detail below. Before that, and to the best of our knowledge, the only existing regional housing series for Spain cover only short periods of time and are not quality-adjusted.

We capitalize on the fact that the real estate ad section in newspapers grew exponentially after 1960 with the legalization of apartment sales to build our own long-run hedonic house price indices for Barcelona and Madrid.[220] As a result, most of our long-run house price series for both Barcelona and Madrid are composed of new series. We did not find newspapers with a sufficient ad coverage to build a long-run index for Valencia.

1.0.11.1 Barcelona

House Price Series. For the period between 1954 and 2008 we build a yearly hedonic house price index for the city of Barcelona based on asking prices from the real estate ad section of the newspaper *La Vanguardia*. In total we collected 12,227 observations for apartments and multi-family houses, which contain information on the asking price, the location and the size of the dwelling.[221] To control for the different locations of the apartments, we include district fixed effects, where we use the official borders of ten districts of the city of Barcelona.[222] As mentioned in the introduction to the Data Appendix on Spanish cities, before 1960 there were very few sales of apartments. As a result, we had to build different house price indices for Barcelona, since the number of observations of apartments and multi-family houses changed considerably over time. Our index only starts in 1954, because the newspapers ad section had very few real estate ads for the years between 1950 and 1954.

For the period between 1954 and 1965 we built a time-dummy hedonic index based on multi-family house sales ("*Torres*") by regressing the log asking prices on the time dummies, district fixed effects and on the following set of controls: number of rooms, number of bathrooms and dummy variables for multiple other features (whether the dwelling has a kitchen, heating or balcony).

220. Before 1960 in Spain the market for apartments was practically non-existent. However, after the introduction of the law *Ley de Propiedad Horizontal* in 1960, the market for apartments started growing exponentially.
221. We winsorize the asking prices at the 1% by year.
222. The districts are: Ciutat Vella, Eixample, Gracia, Horta-Guinardó, Les Corts, Nou Barris, Sant Andreu, Sant Martí, Sants-Montjuic, Sarria-Sant Gervasi.

For the period between 1958 and 1965 we built a time-dummy hedonic index based on multi-family house ads ("*Torres*") and on apartment ads. The reason for this is that for this specific time period the number of observations we were able to collect for each dwelling type is relatively low. As a result, we pool the two different types of dwellings together and run the same regression as above, but now we also include a dummy for the dwelling type.

For the period between 1965 and 2008 we built a three-year rolling-window time-dummy hedonic index by regressing the log asking price on the time dummies, district fixed effects and on the following set of controls: number of rooms, number of bathrooms and dummy variables for multiple other features (whether the dwelling has a kitchen, garden, garage, heating, balcony or whether it was on the top floor of the building).

The *Spanish Institute of Statistics* (INE) publishes house price indices for different Spanish regions since 2007.[223] INE uses data on transaction prices of apartments and single-family houses and dwelling characteristics from the Spanish notaries' data set, which includes information on approximately the universe of transactions in Spain. INE uses these data to build an imputed hedonic index for different dwelling types. The imputed indices are then aggregated using the number of transactions as weights and transformed into a single index using a chained Laspeyres approach.

The Ministry of Development (*Ministerio de Fomento*) published the average dwelling price per square meter for the region of Madrid between 1987 and 2004. The data come from different credit institutions for both new and existing residential dwellings. The price estimates are not quality-adjusted.

In the statistical yearbooks of the city, the *Barcelona City Council* published estimates of average house prices of existing dwellings, i.e. excluding newly built dwellings, for the period between 1975 and 1991. The data were collected from newspapers.

We also calculated yearly average house prices using the total number and total value of residential dwellings transacted in Barcelona for the period between 1950 and 1960. We used the data from the notaries' yearbook (*Anuario de la Dirección General de los Registros y del Notariado*), which contains summary statistics on the universe of real estate transactions recorded by notaries in Spain throughout the year for different autonomous communities (*Comunidades Autonomas*). Due to the lack of quality adjustments, we build a three-year moving average.

Table 1.O.38 summarizes the components of our final house price index. From 1950 to 1954 we use the index based on average prices from the notaries' yearbook. This series is not quality-adjusted, but it is, to the best of our knowledge, the only existing series for this period. From 1954 to 1958 we use the hedonic index based

223. The index is built for 19 *Comunidades Autonomas*, which are political and administrative divisions of Spain.

on multi-family ads. We do use this index until 1965, because the number of multi-family houses in the ad section decreases substantially from 1960 onward. From 1958 to 1965 we use the hedonic index based on both apartments and multi-family houses. From 1965 to 2008 we rely on the three-year rolling window index own based solely on apartment ads. Although our hedonic series are based on asking prices, they are the only continuous series for this period which are quality-adjusted. From 2008 onward, we use the official house price index from INE.

Table 1.O.38. Final house price index for Barcelona

PERIOD	SOURCE	DESCRIPTION
1950-1954	Own compilation	*Type(s) of dwellings*: Owner-occupied dwellings; *Type of data*: Transaction prices from the notaries; *Method*: Simple moving-average.
1954-1958	Own compilation	*Type(s) of dwellings*: Multi-family houses; *Type of data*: Asking prices from *La Vanguardia*; *Method*: Time dummy hedonic series.
1958-1965	Own compilation	*Type(s) of dwellings*: Multi-family houses and apartments; *Type of data*: Asking prices from *La Vanguardia*; *Method*: Time dummy hedonic series.
1965-2008	Own compilation	*Type(s) of dwellings*: Apartments; *Type of data*: Asking prices from *La Vanguardia*; *Method*: Rolling-window hedonic series.
2008-2018	INE (2021b)	*Type(s) of dwellings*: Apartments and single-family houses; *Type of data*: Transaction prices from the notaries' database; *Method*: Chained Laspeyres imputed hedonic index.

Rent Series. The *Spanish Institute of Statistics* (INE) publishes the rent component of the Consumer Price Index regularly for different regions of Spain at least since 1947. For the pre-1985 period INE published the rent indices at the city-level for all province capitals. Since 1985 INE has been publishing the rent indices for all autonomous communities (*Comunidades Autonomas*). And since 2002 INE also publishes rent indices at the province level. The rent index is based on rent prices collected in the Survey on the Active Population (*Encuesta de Población Activa*) from INE, which relies on a rotating sample. This allows INE to use a matched-model approach to calculate average rent changes for the same dwellings over time. As a result, the rent series is mainly composed of existing rental contracts and very little influenced by the values of new rents. Spain introduced rent controls in the 1930s, which lasted until the mid-1960s. Newly constructed buildings were to a large extent exempted from these rent controls and, as a result, the official rent index does not reflect the evolution of rents in the non-controlled rental market. We collected the CPI rent component index using the data from various editions of the Spanish statistical yearbook (*Anuario Estadístico de Espana*).

The department of statistics of the city of Barcelona (*Departament d'Estadística i Difusió de Dades. Ajuntament de Barcelona*) has been publshing the average rent per square meter for new rental contracts in the city of Barcelona since 2000. The averages are based on the universe of new rental contracts, which are collected by the Catalan land institute. In Catalunya all deposits of urban rental contracts must be deposited in the Catalan land institute (*Institut Català del Sòl*).

Table 1.O.39 summarizes the components of our final rent index. To the best of our knowledge there do not exist other historical rent series for Barcelona. As a result we rely for the complete period between 1950 and 2000 on the CPI rent component series from INE. This index measures the evolution of rent prices in Barcelona for the period between 1950 and 1985. For the post-1985 period the index measures the evolution of rent prices in Catalunya. Since Barcelona is by far the largest and most expensive city in the autonomous community Catalonia, we expect the rent series to be a good approximation of the actual rent evolution in the city of Barcelona.[224] From 2000 onward, we rely on the average rent per square meter from the department of statistics of the city of Barcelona. Although this indicator does not fully control for quality changes in the samples, it covers the city of Barcelona and takes into account new rental contracts. A comparison with the index from INE, shows that it grows more for the period between 2000 and 2018 and it shows cyclical variability around the 2007 financial crisis, which is something that is missing in the index from INE.

Table 1.O.39. Final rent index for Barcelona

PERIOD	SOURCE	DESCRIPTION
1950-2000	INE (2021a)	*Type(s) of dwellings*: Renter-occupied dwellings; *Type of data*: Rent prices from survey; *Method*: Matched-model approach.
2000-2018	Difusió de Dades. Ajuntament de Barcelona (various years)	*Type(s) of dwellings*: Renter-occupied dwellings; *Type of data*: Rent prices from the Catalan land institute; *Method*: Average rent per square meter.

Rental Yield Series. Our main benchmark for Barcelona is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to the alternative

224. In 2011, from the 7,519,843 people living in the autonomous community Catalonia, 5,522,565 lived in the Province Barcelona and still 1,611,013 in the municipality of Barcelona (Source: INE, population and housing census 2011.

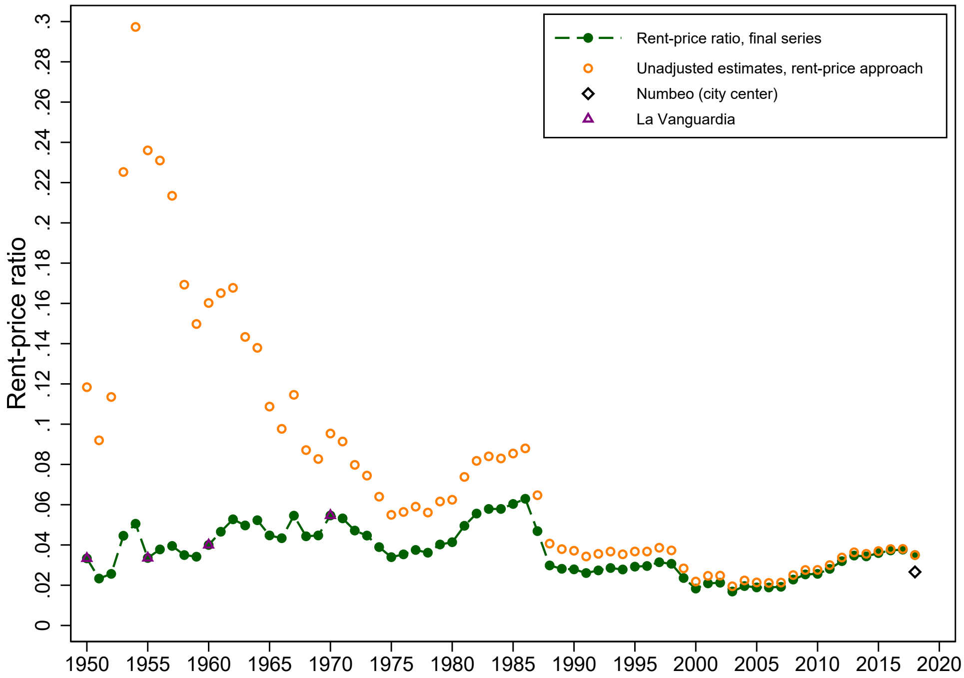

Figure 1.O.23. Barcelona: plausibility of rental yields

benchmark we collected for 2018 from *Numbeo.com*. According to *Numbeo.com* the gross residential yield in the city center of Barcelona in 2018 was 3.5%, to which we discount one-third costs, which gives us a net yield estimate of 2.7%. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.23.

As discussed above, the rent series from INE is mainly composed of existing rents, thereby ignoring to a great extent the evolution of new rents, which can lead to biases in periods in which newly constructed buildings are excluded from rent freezes. In contrast, our house price index captures both the evolution prices of existing dwellings and the evolution of prices of new dwellings. This could potentially create a bias in our rental yield series. Moreover, the rent series covers the entire autonomous community Catalonia, whereas the house price series focuses on the city of Barcelona for most time periods. This might also bias the rental yield series. To check whether this is the case we collected rental yield benchmarks from the newspaper *La Vanguardia* for the beginning of our sample period. We collected on average 30 observations per year, for which we had both the asking price and gross rental income for the same multi-family house. Using these data we build average rental yields for the years 1950, 1955, 1960 and 1970.[225] We then adjust the gross estimates for one-third costs and get the net yield estimates, which can be seen in Figure 1.O.23. The net yield estimates from *La Vanguardia* lie substantially below our unadjusted rental yield series. Since this difference is quite large and probably reflects the above-mentioned bias in our unadjusted rental yield series, we use the historical estimates to benchmark our series.

This gives us the adjusted final rental yield series — the green-circled line in Figure 1.O.23.

1.O.11.2 Madrid

House Price Series. For the period between 1950 and 2010 we build a yearly hedonic house price index for Madrid based on asking prices from the real estate ad section of the newspaper *ABC*. In total we collected 12,767 observations, which contain information on the asking price, the location and the size of the dwelling. As we explain in more detail below, the types of dwelling included in our data set as well as the variable we use to control for the size of the dwellings changes over time.[226] Additionally, our number of observations increases substantially for more recent decades. To account for these differences over time, we built different indices for subperiods between 1950 and 2010. For all these indices we include district fixed effects, where we use the official borders of 20 districts of the city of Madrid to assign the observations.[227] Since the months for which we have data change over time we also control for the quarter in which the ad was posted. While until 1975 most of the ads included information on the number of rooms in the dwelling, this changed in the post-1975 period, where most ads include the total square meters of the dwelling instead.[228]

For the period between 1950 and 1990 we built both a five-year rolling-window hedonic index as well as an adjacent-period hedonic index by regressing the log asking price on year dummies, location and quarter fixed effects and on the following set of controls: number of rooms, type of dwelling (single-family, duplex or apartment), number of bathrooms, and dummies for other features (whether the dwelling has a kitchen, garden, garage, heating or air conditioning).

225. The median yields very similar results.
226. We winsorize the asking prices at the 1% by year.
227. The districts are: Centro, Arganzuela, Retiro, Salamanca, Chamartín, Tetuán, Chamberí, Fuencarral-El Pardo, Moncloa-Aravaca, Latina, Carabanchel, Usera, Puente de Vallecas, Moratalaz, Ciudad Lineal, Hortaleza, Villaverde, Villa de Vallecas, Vicálvaro and San Blas-Canillejas Barajas.
228. In the post-1975 sample we include observations for which we estimated the number of square meters. For the estimation we use the coefficient from a simple linear regression of size in square meters on number of rooms for a sample of observations for which we were able to collect both variables. Excluding the observations for which we estimate the size in square meters only changes our indices slightly.

For the period between 1975 and 2010 we built an adjacent-period hedonic index, which is equal to the index for the period between 1950 and 1990 with one exception: instead of controlling for the number of rooms, we control for the log squared meters of the dwelling. The reason for this is that after 1975 most ads included the square meterage of the dwelling instead of the number of rooms. In order not to lose the observations for which we do not have square meterage but only the number of rooms, we predict the square meterage based on the observations for which we have both the number of rooms and the square meterage.

The *Spanish Institute of Statistics* (INE) publishes house price indices for different Spanish regions since 2007. INE uses data on transaction prices of apartments and single-family houses and dwelling characteristics from the Spanish notaries' data set, which includes information on approximately the universe of transactions in Spain. INE uses these data to build an imputed hedonic index for different dwelling types. The imputed indices are then aggregated using the number of transactions as weights and transformed into as single index using a chained Laspeyres approach.

The Ministry of Development (*Ministerie de Fomento* published the average price per square meter for the region of Madrid between 1987 and 2004. The data come from different credit institutions for both new and existing residential dwellings. The price estimates are not quality-adjusted.

The city of Madrid also published average prices of residential dwellings for the period between 1960 and 1974 for the metropolitan area of Madrid. The estimates are based on a survey conducted by the planning commission of the city of Madrid (*Comisión de Planeamiento y Coordinación del Área Metropolitana de Madrid*), which collected prices of both privately-owned houses and officially sponsored houses.

The real estate company *Tecnigrama* published average prices per square meter for new dwellings in the city of Madrid between 1976 and 1990.

Table 1.O.40 summarizes the components of our final house price index. From 1950 to 2010 we rely on our own index based on data from *ABC*. More precisely, from 1950 to 1960 we use the five-year rolling-window hedonic index, because the number of observations per year is not as high as in later years, from 1960 to 1980 we use the adjacent period hedonic index, in which we control for the number of rooms, and from 1980 to 2010 we rely on the adjacent period index, in which we control for the total square meters. Although this series is based on asking prices, it is the only continuous series, which is quality-adjusted. From 2010 onward, we use the official house price index from INE.

Rent Series. As we explain in Section 1.O.11.1 above for Barcelona, the *Spanish Institute of Statistics* (INE) publishes the rent component of the Consumer Price Index regularly. The index is based on rent prices collected in the Survey on the Active Population (*Encuesta de Población Activa*) from INE, which is based on a rotating sample. This allows INE to use a matched-model approach to calculate average rent

Table 1.O.40. Final house price index for Madrid

PERIOD	SOURCE	DESCRIPTION
1950-2010	Own compilation	*Type(s) of dwellings*: Apartments and single-family houses; *Type of data*: Asking prices from *ABC* ; *Method*: Rolling-window and adjacent period hedonic indices.
2010-2018	INE (2021b)	*Type(s) of dwellings*: Apartments and single-family houses; *Type of data*: Transaction prices from the notaries' database ; *Method*: Chained Laspeyres imputed hedonic index.

changes for the same dwellings over time. As explained above, this official rent index does not reflect the evolution of rents in the non-controlled rental market. We collected the CPI rent component index using the data from various editions of the Spanish statistical yearbook (*Anuario Estadístico de Espana*).

From 2005 onward the real estate website *Idealista.es* has been publishing the average rent per square meter in the city of Madrid.[229] The estimates are based on the average asking rent of all residential rental units located in the city of Madrid, which can be found in the website. We use these estimates of average rent to build a rent index for the city of Madrid between 2005 and 2018.

Table 1.O.41 summarizes the components of our final rent index. To the best of our knowledge there do not exist other historical rent series for Madrid. As a result we rely for the complete period between 1950 and 2005 on the CPI rent component series from INE. This index measures the evolution of rent prices in the city of Madrid for the period between 1950 and 1985. From 1985 to 2002 the index measures the evolution of rent prices in the autonomous community of Madrid. The autonomous community Madrid coincides with the Province of Madrid and approximately covers the metropolitan area of Madrid.[230] Hence, we expect the rent series to be a very good approximation of the actual rent evolution in the city of Madrid. From 2002 to 2005 the index measures the rent developments in the province of Madrid. From 2005 to 2018 we rely on the index from *Idealista.es*, since this index covers new rental contracts and focuses specifically on the city of Madrid.

Rental Yield Series. Our main benchmark for Madrid is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to the alternative benchmark we collected for 2018 from *Numbeo.com*. According to *Numbeo.com* the gross residential rental yield in the city center of Madrid in 2018 was 4.37%, to

229. The series can be found in the website.
230. In 2011, from the 6,421,874 people living in the autonomous community Madrid, 3,198,645 lived in the municipality of Madrid (Source: INE, population and housing census 2011.

Table 1.O.41. Final rent index for Madrid

PERIOD	SOURCE	DESCRIPTION
1950-2005	INE (2021a)	*Type(s) of dwellings*: Renter-occupied dwellings; *Type of data*: Rent prices from survey; *Method*: Matched-model approach.
2005-2018	*Idealista.es*	*Type(s) of dwellings*: Renter-occupied dwellings; *Type of data*: Asking rent prices from online advertisements; *Method*: Average rent per square meter.

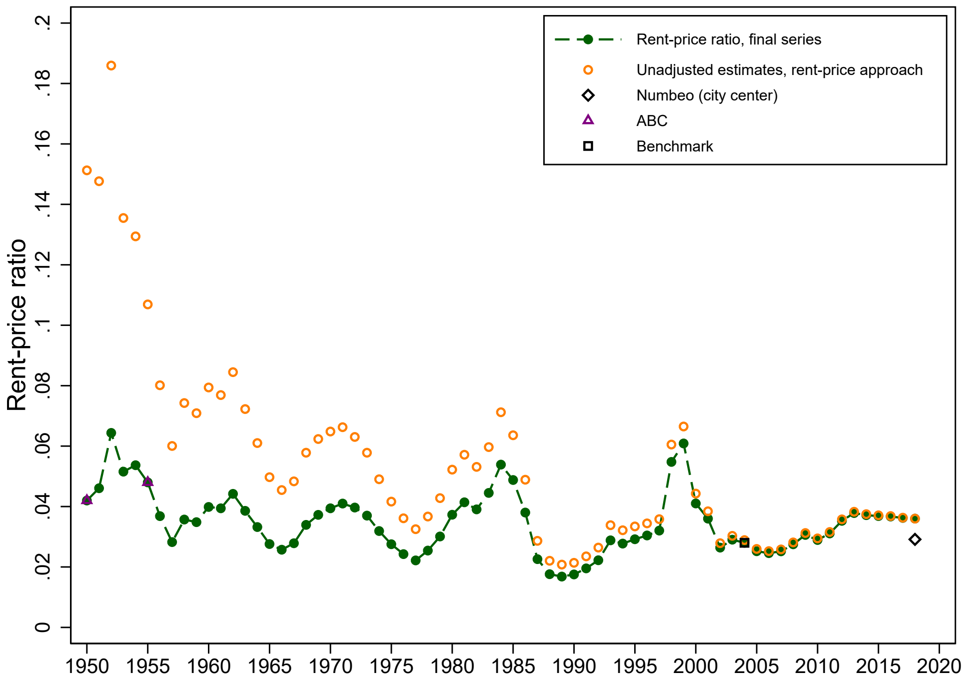

Figure 1.O.24. Madrid: plausibility of rental yields

which we discount one-third costs, which gives us a net yield estimate of 2.9%. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.24.

We also plot a net yield benchmark from *MSCI* for 2014, which is exactly on our unadjusted rental yield series.

As discussed above, the rent series from INE is mainly composed of existing rents, thereby ignoring to a great extent the evolution of new rents, which can lead to biases in periods in which newly constructed buildings are excluded from rent freezes. In contrast, our house price index captures both the evolution prices of existing dwellings and the evolution of prices of new dwellings. This could potentially create a bias in our rental yield series. To check whether this is the case we collected rental yield benchmarks from the newspaper *ABC* for the beginning of our sample period. In total we collected 60 observations, for which we had both the asking price and gross rental income for the same multi-family house. Using these data we build average rental yields for the years 1950 and 1955.[231] We then adjust the gross estimates for one-third costs and get the net yield estimates, which can be seen in Figure 1.O.24. The net yield estimates from *ABC* lie substantially below our unadjusted rental yield series. Since this difference is quite large and probably reflects the above-mentioned bias in our unadjusted rental yield series, we use the historical estimates to benchmark our series.

This gives us the adjusted final rental yield series—the green-circled line in Figure 1.O.24.

231. The median yields very similar results.

1.O.12 Sweden

Stockholm and Gothenburg were Sweden's largest cities already by 1900, making up a bit less than six and three % of the country's population respectively. Both are the center of Sweden's now two largest metropolitan regions. Both cities have been subject to detailed and high-quality long-run house price studies, whereas consistent rental data are not readily available. The next largest cities in 1900 were Malmö and Norrköping, whose absolute population, however, were 60,000 or less. We are not aware of existing high-quality long-run price or rent data for these cities.

1.O.12.1 Gothenburg

House Price Series. The long-run house price series for Gothenburg is a high-quality series created by various authors and *Statistics Sweden*. For the time period 1875-1957, we use the index constructed by Bohlin (2014). The data he used are sourced from property tax valuations for houses and combined with purchasing prices from a ledger of properties. The index is built using the SPAR method. From 1957 until 2013, we rely on the index on houses in Gothenburg published in Edvinsson, Blöndal, and Söderberg (2014). The authors used data on small houses from *Statistics Sweden* and built a house price index using the SPAR method. Since 2013, the data we use are from *Statistics Sweden* on transaction and tax valuations of buildings with one or two dwellings, again using the SPAR method. The components of our final house price index are summarized in Table 1.O.42.

Table 1.O.42. Final house price index for Gothenburg

PERIOD	SOURCE	DESCRIPTION
1875-1957	Bohlin (2014)	*Type(s) of dwellings*: Houses; *Type of data*: Property tax valuations and purchasing prices from the *Lagfartsprotokoll*; *Method*: SPAR method.
1957-2012	Edvinsson, Blöndal, and Söderberg (2014)	*Type(s) of dwellings*: Small houses; *Type of data*: Tax valuations and purchasing prices from Statistics Sweden; *Method*: SPAR method.
2013-2018	Statistics Sweden	*Type(s) of dwellings*: One- or two-dwelling buildings; *Type of data*: Individual transaction and tax valuation data; *Method*: SPAR method.

Rent Series. For the rental series, we make use of three different sources: prior to 1950 we draw on the rent surveys for benchmark years reported in Gothenburg's statistical yearbook, using the average rent for a three-room dwelling. We interpolate missing years by using the rent component of the national CPI-index.

Between 1950 and 1978, we collected ads for rental housing in Gothenburg's most important local newspaper, the *Göteborgposten*, which published an ad section covering the local rental market ("*hyresmarknaden*"). This contained predominantly two rental market segments: offers for housing exchanges (due to housing shortages throughout this period) and offers for cooperative rental units ("*insatslägenheter*"). We scanned these relevant pages between 1950 and 1964 from microfilm in the Gothenburg university library and downloaded digitized versions from the website *tidningar.kb.se* for the later period. We extracted all ads containing full information on price, rent and location, yielding a total of 2,181 observations. We then estimated a hedonic price regression of log rent levels using the time-dummy approach with number of rooms, type of offer, quality (new/old) and location as control variables. For the location variable, we recoded the neighborhood and addresses mentioned in the ads into the historical administrative division of ten city districts (plus periphery). The adjusted R^2 is 0.857.

Lastly, we connected the newly constructed series to those reported by *Statistics Sweden* (SCB) on the Greater Gothenburg region, using the three-room average annual rents for existing contracts from 1978 until 1990, the average annual rent per square meter for existing contracts for renting apartments in Greater Gothenburg between 1990 and 1994 and the average rent per square meter for three-room apartments for both existing and new contracts in Gothenburg since 1994. The data are reported in the "*Bostads- och hyresundersökningen serie BO*" for the historical time period and on the SCB website for more recent years. Table 1.O.43 summarizes the components of our final rent index.

Table 1.O.43. Final rent index for Gothenburg

PERIOD	SOURCE	DESCRIPTION
1914-1950	Statistics Sweden	*Type(s) of dwellings*: Three-room dwellings; *Type of data*: Municipal rent surveys; *Method*: Average annual rents (interpolated).
1950-1978	Own series	*Type(s) of dwellings*: Apartments; *Type of data*: Newspaper ads from *Göteborgposten*; *Method*: Hedonic rent index.
1978-1990	Statistics Sweden	*Type(s) of dwellings*: Three-room dwellings; *Type of data*: Rent surveys ("*Hyresräkning*"); *Method*: Average annual rents.
1990-1994	Statistics Sweden	*Type(s) of dwellings*: Apartments in existing stock (Greater Gothenburg); *Type of data*: Rent survey from Statistics Sweden; *Method*: Average annual rents per sqm.
1994-2018	Statistics Sweden	*Type(s) of dwellings*: Existing and new contracts for apartments with three rooms; *Type of data*: Rent survey from Statistics Sweden; *Method*: Average annual rents per sqm.

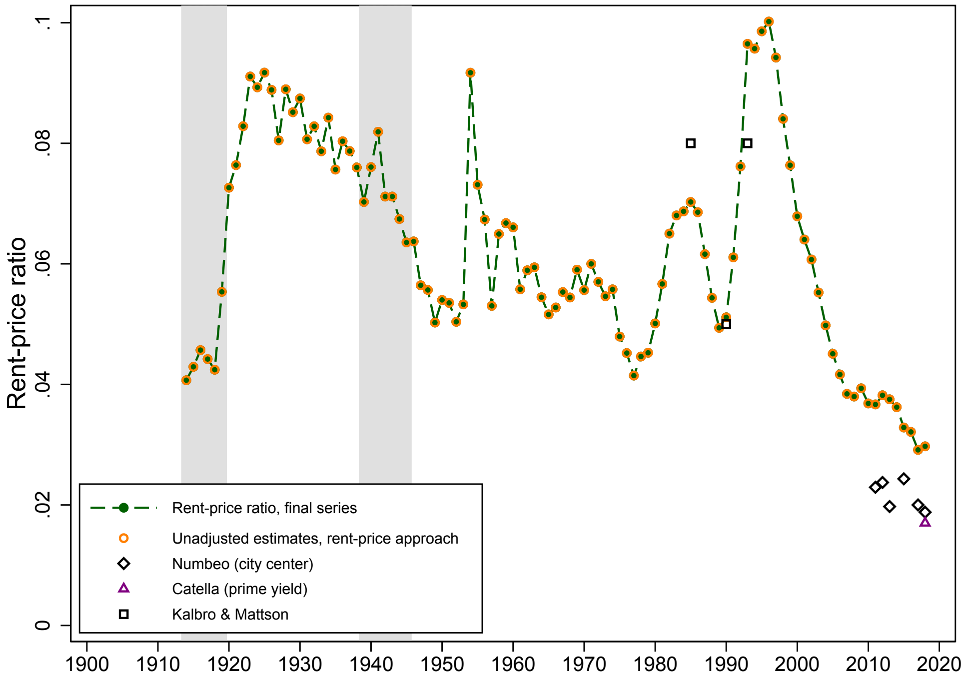

Figure 1.O.25. Gothenburg: plausibility of rental yields

Rental Yield Series. Our main benchmark for Gothenburg is taken from *MSCI*, as described in the main paper. Applying the rent-price approach to this benchmark results in the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.25.

We collected two additional benchmarks for 2018. First, we use the benchmark for the city-center of Gothenburg from *Numbeo.com*, which we adjust to capture net rental yields by subtracting one-third following Jordà et al. (2019). Second, we use the prime yield for Gothenburg from *Catella* reports.[232] Both benchmarks are somewhat below but close to our main benchmark from *MSCI*. We use the benchmark by *Numbeo.com* as our alternative benchmark in the robustness section of the main paper. Additionally, we collected benchmarks from *Numbeo.com* for the years from 2011 to 2017. These benchmarks show a similar pattern compared to our long-run series.

We also collected historical rental yield benchmarks for Gothenburg from Kalbro and Mattsson (1995) for the years 1985, 1990 and 1993. These benchmarks are very close to our unadjusted long-run rental yield series. The unadjusted series shows a long-term decline of rental yields after the 1920s. With the introduction of rent-controls, there were spikes after the two World Wars and a considerable spike

232. Source: Catella, "European commercial residential market map 2018".

around the burst of the 1990 housing bubble. Given that our unadjusted rental yield series is close to the historical benchmarks and shows probable patterns given the historical background, we do not adjust our long-run series.

1.O.12.2 Stockholm

House Price Series. The long-run house price index for Stockholm is composed of three different series and largely following the seminal work by Edvinsson, Blöndal, and Söderberg (2014). Between 1875 and 1956, this index is calculated using the SPAR method and relies on the property tax valuations from the *Stockholms adresskalender* as well as purchase prices from the register of certificates of title to properties, which is in the archives of the Stockholm Magistrates' Court. From 1957 onward until 2012, the authors use the already constructed index by *Statistics Sweden*. The index is built using the SPAR method also using data on tax valuation and purchase prices for small houses and apartment buildings. We rely on the index on houses. Finally, the most recent data are from *Statistics Sweden*, which provides an index built using the SPAR method based on individual transaction and tax valuation data on one- or two-dwelling buildings. Table 1.O.44 summarizes the components of our final rent index.

Table 1.O.44. Final house price index for Stockholm

PERIOD	SOURCE	DESCRIPTION
1875-1956	Edvinsson, Blöndal, and Söderberg (2014)	*Type(s) of dwellings*: Houses; *Type of data*: Property tax valuations and purchase prices from *Stockholms adresskalender*; *Method*: SPAR method.
1957-2012	Edvinsson, Blöndal, and Söderberg (2014)	*Type(s) of dwellings*: Small houses; *Type of data*: Index from Statistics Sweden; *Method*: SPAR method.
2013-2018	Statistics Sweden	*Type(s) of dwellings*: One- or two- dwelling buildings; *Type of data*: Individual transaction and tax valuation data; *Method*: SPAR method.

Rent Series. The long-run rental series are based on two different sources (Table 1.O.45): First, Stockholm's statistical yearbook, which provides benchmark rents for apartments of various room sizes for the city center of Stockholm that we use to build a stratified Fisher index. Strata are defined by the number of rooms of the dwelling. For the period between 1894 and 1914 and the period between 1943 and 1960 there are data every five years. For these two periods we construct a non-chained Fisher Index.[233] For the period in between 1915-1942, there are no missing data, so we construct a chained Fisher index.

The second source starts in 1960. Here we can use the regional break-down of nationally surveyed rental market statistics which are available for the region of Stockholm by different room classes on a yearly basis, published as the "*Bostads- och hyresundersökningen serie BO*" in Stockholm's statistical yearbooks and by *Statistics Sweden*. Strata are defined by the number of rooms in the dwelling. For the period between 1960 and 1978 there are data only in 1960, 1965, 1968 and 1978. For this periods we construct a non-chained Fisher Index. The missing data between 1960 and 1968 are linearly interpolated. Between 1968 and 1978 we use two different rent measures published in Stockholm's statistical yearbooks for interpolation. Between 1968 and 1970, we use the rent per room in the city center and the suburbs of Stockholm. We calculate the increase between 1968 and 1970 for both locational categories and then take a simple average. Between 1970 and 1978 we use yearly data on the rent in multi-family houses built by private enterprise with state housing loans. We calculate a chained Fisher stratification index and use this index for interpolation. For the years after 1978 we construct a chained Fisher stratification index.

Table 1.O.45. Final rent index for Stockholm

PERIOD	SOURCE	DESCRIPTION
1894-1960	Yearbook of the city of Stockholm	*Type(s) of dwellings*: Apartments of different room sizes (city center); *Type of data*: Municipal rent surveys; *Method*: Stratified Fisher Index (interpolated).
1960-2019	Yearbook of the city of Stockholm & Statistics Sweden	*Type(s) of dwellings*: Apartments of different room sizes; *Type of data*: Surveys by Statistics Sweden (Hyresräkning); *Method*: Stratified Fisher index (interpolated for earlier years).

Rental Yield Series. Our main benchmark for Stockholm is taken from *MSCI*, as described in the main paper. Applying the rent-price approach to this benchmark results in the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.26.

We collected two additional benchmarks for 2018. First, we use the benchmark for the city-center of Stockholm from *Numbeo.com*, which we adjust to capture net rental yields by subtracting one-third following Jordà et al. (2019). Second, we use

233. We use the first year of the respective period as base year. Years in-between are linearly interpolated.

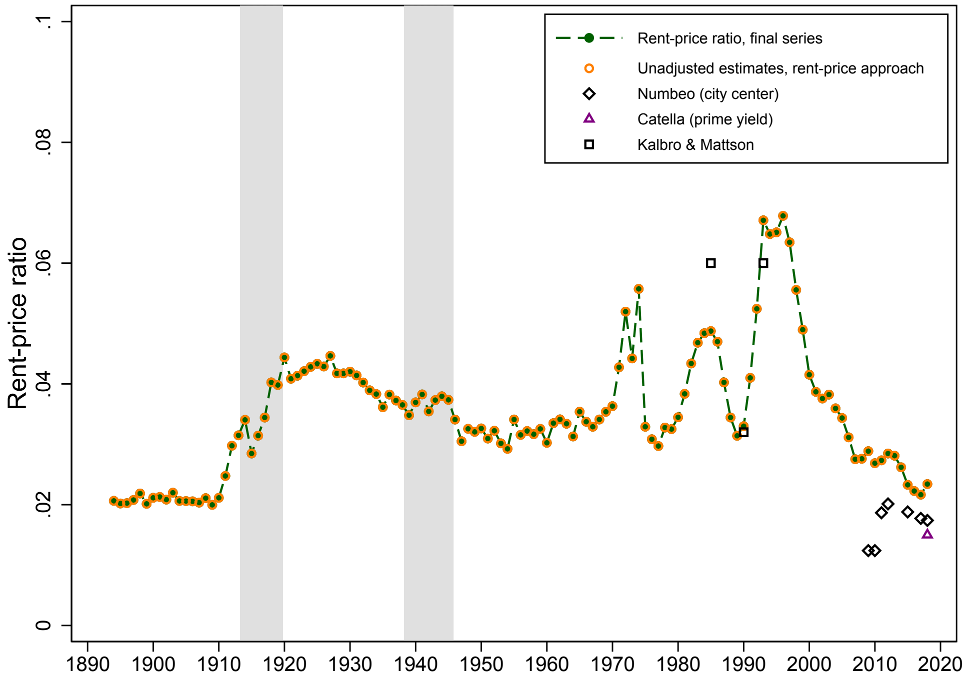

Figure 1.O.26. Stockholm: plausibility of rental yields

the prime yield from *Catella* reports.[234] Both benchmarks are somewhat below but close to our main benchmark from *MSCI*. We use the benchmark by *Numbeo.com* as our alternative benchmark in the robustness section of the main paper. Additionally, we collected benchmarks from *Numbeo.com* for the years from 2009 to 2017. These benchmarks are also below our unadjusted series.

We also collected historical rental yield benchmarks for Stockholm from Kalbro and Mattsson (1995) for the years 1985, 1990 and 1993. These benchmarks are very close to our unadjusted long-run rental yield series. Given that our unadjusted rental yield series is close to the historical benchmarks and shows similar patterns as the series for Gothenburg, we do not adjust our long-run series.

234. Source: Catella, "European commercial residential market map 2018".

1.0.13 Switzerland

The five largest cities in Switzerland in 1900 were in descending order: Zurich, Geneva, Basel, Bern, and Lausanne. All of these cities covered more than 1% of the country's population. We have, however, not been able to find sufficient data to construct long-run house price or rent series for Geneva and Lausanne. By including Zurich, Basel and Bern, we still cover almost 10% of Switzerland's population in 1900.

To the best of our knowledge, there do not exist any compiled house price series on city-level from public sources in Switzerland. Publications from city-level statistical offices within major cities do, however, often contain aggregated housing sales data. In many cases, these data are given for different (inner-city) locations, such that it is possible to control for sample shifts within the location of sold properties. As location is maybe the most important quality characteristic for houses and, within cities, other highly relevant characteristics like size, housing types and construction period are highly correlated with location,[235] this quality control probably minimizes the bias in the house price series.

Apart from these sources, private companies are able to provide regional real estate indices for sale. These indices are typically constructed using private micro-level data sets. The methods are, however, in many cases not made transparent. Due to missing alternatives, we had to rely on such data for Basel and Bern for the most recent decades.

Regarding rent series, statistical offices of large cities also regularly published city-level rent series. These have often been calculated to construct city-level CPI series and are based on reliable and transparent methods.

We discuss the construction of our long-run city-level series in more detail below. The discussion is structured by cities and within cities, by price series, rent series and rental yield series.

1.0.13.1 Basel

House Price Series. To build the long-run house price index for Basel, we use various statistical publications. For much of the period, these publications provide data by district, such that we are able to control for sample shifts in the location of sold properties. For some periods, however, data are only given for the whole Basel-city region ("Kanton Basel-Stadt"). Moreover, in 1982, the statistical office stopped publishing prices of sold properties for a considerable time period. To get a long-run

235. This is especially true for Swiss cities, because locational zoning restrictions imply that only buildings of specific types are allowed in specific parts of the city. For Zurich, we did compile an experimental index using house price data disaggregated by these construction zones ("*Bauzonen*"). The resulting index is very similar to an index using location bins instead.

index, we, therefore, had to rely on a private house price index provided by *Wüest Partner*. We describe the different parts of the index in more details below.

For the last four decades, to the best of our knowledge only insufficient house price data is available for Basel from public sources. This means that we have to rely on private house price indices. We use a transaction price index for single-family houses provided by *Wüest Partner*. This index is constructed using hedonic methods and covers the region Basel-City ("Kanton Basel-Stadt"). In addition to the municipality Basel, this region also covers the two considerably smaller municipalities Riehen and Bettingen, which are part of the MS-region Basel. The index starts in 1985.

Prior to this year, we rely on aggregate house price data from statistical yearbooks.[236] These data cover all voluntary sales of developed lots within the region Basel-City.[237] From 1921 to 1963, the data are given separately for the 19 districts ("*Quartiere*") of the Basel municipality as well as the municipalities of Riehen and Bettingen.[238] We use average price per transaction by district to calculate a chained Fisher-type stratification index following Eurostat (2013).[239] Thereby, we control for locational shifts over time within the sample of sold developed lots. Between 1964 and 1981, the yearbooks only contain average price per transaction for the entire Basel-City region. We therefore have to rely on these averages to construct the house price index for this period. Data for the years 1982 to 1984 as well as for the year 1926 are missing. To link the index ending in 1981 to the index starting in 1985, we use the average price per sale of developed lots by district for 2006 from statistical yearbooks.[240] 2006 is the earliest year for which the data were published again. To control for locational shifts within the sample of transacted properties, which is probably even more important over a long time period, we link the data to the data in 1963 and again calculate a Fisher-type stratification index. We use this index and our yearly indices until 1981 and starting in 1985 to calculate the implied increases in house prices between 1981 and 1985. Afterwards, we linearly interpolate missing years to calculate yearly housing returns.

236. "*Statistisches Jahrbuch des Kantons Basel-Stadt*" (Volumes 1921-1982).
237. "*Handänderungen von Freihandverkäufen bebauter Grundstücke*".
238. Approximately 10% of all sales in the region Basel-City have been in the municipalities of Riehen and Bettingen between 1921 and 1963. We still include these municipalities, because they are in commuting distance to the center of Basel and to be consistent with earlier and later periods.
239. To calculate the chained index, for every pair of consecutive years, we drop all districts that feature less than three sales in one of the two years. This ensures that the average is a meaningful characteristic and the influence of outliers is reduced.
240. Source: "*Statistisches Jahrbuch des Kantons Basel-Stadt*" (2006))

Prior to 1921, we again have to rely on average price per sold developed lot in the Basel-City region. The data start in 1912 and are collected from a publication of the national statistical office.[241]

Table 1.O.46 summarizes the components of our final house price index.

Table 1.O.46. Final house price index for Basel

PERIOD	SOURCE	DESCRIPTION
1912-1921	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales within Basel-City region from statistical publication; *Method*: Average price per transaction.
1921-1963	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated by district from yearbooks; *Method*: Stratification.
1964-1981	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales within Basel-City region from yearbooks; *Method*: Average price per transaction.
1985-2018	Wüest Partner	*Type(s) of dwellings*: Single-family houses; *Type of data*: Private transaction-level data; *Method*: Hedonic index.

Rent Series. To construct the long-run rent index for Basel, we mainly rely on data published by the statistical office of the Basel-City region ("Kanton Basel-Stadt"). For the last five decades, we use the rent index calculated by the statistical office. For the period before, we use average rent by number of rooms published in the statistical yearbooks. Prior to 1920, we use the rent index for Basel published in Curti (1981).

Starting in 1970, our long-run series is composed of the residential rent index for the Basel-City region published by the statistical office.[242] This index was constructed using a random stratified sample covering 5% of all rented dwellings that have one to six rooms.[243]

Prior to 1970, we use residential rent data published in the statistical yearbooks.[244] To ensure constant quality of the sample used to build the rent index, we only rely on average rents of dwellings built prior to 1920 and after 1940. Between 1954 and 1970, we use the averages for dwellings featuring a bathroom that were built between 1900 and 1920 and had between two and four rooms. We build a

241. Source: "*Die Statistik der hypothekarischen Verschuldung und der Handänderungen (Grundbuchstatistik) in einigen Kantonen*", in "*Schweizeriche Zeitschrift für Volkswirtschaft und Statistik*" *(1930) published by the* "*Eidgenössisches Statistisches Amt*".
242. "*Statistisches Amt des Kantons Basel-Stadt*", Table t09.3.04, last update December 4, 2018.
243. "*Geschichtete Zufallsstichprobe, die 5% der Miet- und Genossenschaftswohnungen mit 1-6 Zimmern umfasst*".
244. "*Statistisches Jahrbuch des Kantons Basel-Stadt*" (Volumes 1925 - 1970).

weighted average for each year over the number of room bins (2-4) using the number of dwellings by number of rooms from the housing census in 1970 as weights. Afterwards, we calculate the increase of the yearly weighted average. As we use the same weights and types of dwellings every year, this procedure minimizes the influence of sample shifts within the sample of rented dwellings. Between 1940 and 1954, we instead use all rented dwellings constructed before 1920 featuring a bathroom but no mansard and having three to four rooms.[245] We use the number of dwellings with three to four rooms from the housing census in 1950 as weights. Between 1925 and 1940, rented dwellings are sampled to match the mixture of old and new flats in the Basel housing stock that have two to five rooms. We use bins by number of rooms and within rooms by number of mansards and build a weighted average using the number of dwellings in the housing census in 1930 as weights. Between 1920 and 1925, we use a sample of dwellings that was sampled repeatedly in all years since 1920 for the same number of rooms (2-5) and number of mansard (0-2+) bins. We use the number of dwellings by number of rooms and number of mansards from 1929 as weights.

For the period between 1890 and 1920, we use the rent index constructed by Curti (1981). Between 1890 and 1912, the author uses newspaper advertisements for three-room apartments without a mansard in blue-collar worker districts. After 1912, he instead relies on apartments advertised through a public institution.[246] He again uses only three-room apartments, but the apartments are sampled from the entire city of Basel. Next, he chains both indices and calculates three-year moving averages. Finally, Curti adjusts his index for the rent increase between housing censuses in 1910 and 1920. Details can be found in the respective publication.

Table 1.O.47 summarizes the components of our final rent index.

Rental Yield Series. In 2018, we used the net rental yield from *MSCI* as our main benchmark as described in the main paper. Applying the rent-price approach to this benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.27. We collected two additional benchmarks for 2018. First, we use the benchmark for the city-center of Basel from *Numbeo.com*, which we adjust to capture net rental yields by subtracting one-third following Jordà et al. (2019). Second, we use the prime yield ("*Spitzenrendite*") for Basel published by *Wüest Partner* in their Swiss market reports.[247] It is calculated as the net initial yield (net earnings/gross purchase price) for fully let prime properties at top locations. We adjust this yield for the vacancy rate in Basel from the same publication. Both benchmarks are somewhat below our main benchmark from *MSCI*. We use the

245. Data for two-room dwellings are missing for some years in between. The data are not given separately anymore for dwellings built between 1900 and 1920 as well as for dwellings built prior to 1920.

246. Rents published in the *Anzeiger des amtlichen Wohnungsnachweises*.

247. "*Immobilienmarkt Schweiz* 2018|4"

Table 1.O.47. Final rent index for Basel

PERIOD	SOURCE	DESCRIPTION
1890-1920	Curti (1981)	*Type(s) of dwellings*: Three-room apartments without a mansard; *Type of data*: Newspapers, advertised dwellings in public institution and housing census; *Method*: Three-year moving average adjusted with housing census data in 1910 and 1920.
1920-1925	Own compilation	*Type(s) of dwellings*: Constant sample of rented dwellings with two to five rooms; *Type of data*: Average rent; *Method*: Weighted average using constant weights.
1925-1940	Own compilation	*Type(s) of dwellings*: All rented dwellings with two to five rooms; *Type of data*: Average rent; *Method*: Weighted average using constant weights.
1940-1954	Own compilation	*Type(s) of dwellings*: Dwellings featuring a bathroom built before 1920 with three to four rooms without mansard; *Type of data*: Average rent; *Method*: Weighted average using constant weights.
1954-1970	Own compilation	*Type(s) of dwellings*: Dwellings featuring a bathroom built between 1900 and 1920 with two to four rooms; *Type of data*: Average rent; *Method*: Weighted average using constant weights.
1970-2018	Statistics Basel	*Type(s) of dwellings*: All rented dwellings with one to six rooms; *Type of data*: Random stratified sample covering 5% of all rented dwellings; *Method*: CPI rent index.

benchmark by *Wüest Partner* as our alternative benchmark in the robustness section of the main paper.

We collected two types of historical benchmarks. First, we use the prime yield again adjusted for the vacancy rate and the net-cash-flow yield ("*Netttocashflowrendite*") for rental apartments published by *Wüest Partner* for 2011.[248] Our long-run series is again above the prime-yield, but somewhat below the net-cash-flow yield for apartments, which seems to be plausible.

Second, we collected rental yield benchmarks from newspaper advertisements for the years 1950 and 1960. We take the mean rental yield adjusted for all costs by subtracting one-third as in Jordà et al. (2019). It proved to be hard to find newspaper advertisements that featured a rental yield or a price-rent ratio for properties in the city of Basel, such that the sample size is very small. Considering the strict rent

248. Source: "*Wuest & Partner Immo-Monitoring 2012|2*" p. 173.

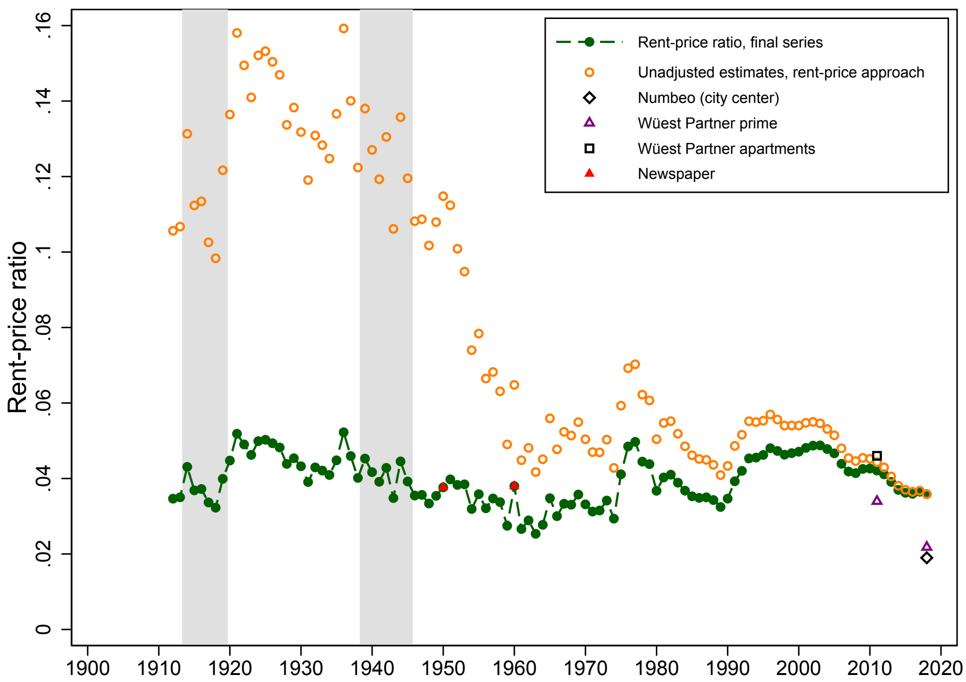

Figure 1.O.27. Basel: plausibility of rental yields

controls in Switzerland during this period,[249] the resulting values are still credible. These rent controls ensured that the variation in rental yields between properties was very small. Indeed, in a public report regarding the rent policy from 1950,[250] the authors describe that the rent in Switzerland was fixed relative to the value of the property. The report states that, after 1946, the outside capital invested into real estate was meant to yield a rate of 3.8%. This value closely matches the newspaper net rental yield benchmark of 3.87% for Basel in 1950.

As the strict rent controls in Switzerland after World War II until the 1960s both makes the newspaper benchmarks more credible and probably induces a bias in our unadjusted long-run rental yield series, we adjust our rental yield series to the newspaper benchmarks in 1950 and 1960. This results in the final rental yield series depicted as the green-circled line in Figure 1.O.27.

249. See e.g. the report "*Die Entwicklung des schweizerischen Mietrechts von 1911 bis zur Gegenwart*" by Helen Rohrbach (2014).
250. "*Die langfristige Neuordnung der Mietpreispolitik*", report of the "*Eidg. Priskontrollkommission (Sub- und Plenarkommission) zuhanden des Vorstehers des Eidg. Volkswirtschaftsdepartements*" (1950).

1.O.13.2 Bern

House Price Series. The long-run house price index for Bern is constructed using various publications by Statistics Bern. For most of the period, the data contain average property prices by district, such that we can control for sample shifts in the location of sold properties. For the earliest two decades, however, the data are only given for the entire city of Bern. Moreover, data for the most recent decades are missing. Hence, we again had to rely on a house price index provided by *Wüest Partner*. Below, we describe in more details how we construct our long-run index and which sources we use.

Like for Basel, we have to rely on private house price indices for the most recent period, because the publication of property prices by the statistical office stops in 2003. We again use a transaction price index for single-family houses provided by *Wüest Partner*. This index is constructed using hedonic methods and covers the MS-region Bern. The index starts in 1985.

Between 1933 and 1985, we use average prices of sold properties from statistical yearbooks.[251] These data cover all voluntary sales of developed lots within the city of Bern.[252] Average prices are given disaggregated by six constant districts ("*Stadtteile*"). We use these to calculate a chained Fisher-type stratification index following Eurostat (2013) using number of transactions by district as weights. In this way we control for locational shifts over time within the sample of sold developed lots. We use the price per transaction instead of the price per square meter, because the price per square meter results in a much noisier series. The reason seems to be that, during the earlier years, some still agrarian developed lots were sold in Bern as can be seen in the yearbooks. These lots had abnormally large areas, such that they bias the average price per square meter considerably. As the number of these lots sold is very low, the average price per transaction is biased considerably less. Data for the year 1939 are missing. We linearly interpolate this year to calculate housing returns.

For the period from 1912 to 1933, we instead had to rely on average price per sold developed lot within the entire city of Bern published by Statistics Bern.[253] We again use price per transaction, because the price per square meter is considerably more volatile probably due to the same reason as described above.

Table 1.O.48 summarizes the components of our final house price index.

Rent Series. To construct a long-run rent index for Bern, we use the rent index produced by Statistics Bern for nearly the entire time period. Only for the period

251. "*Statistisches Jahrbuch der Stadt Bern*" (Volumes 1930-1985).
252. "*Handänderungen von Freihandverkäufen bebauter Grundstücke*".
253. *Statistics Bern*: Table T 5.5.3: "*Stadt Bern: Handänderungen von Grundstücken durch Freihandkäufe 1912-2001*". Original sources according to published table: "*Statistisches Handbuch der Stadt Bern, Ausg. 1935; Statistisches Amt der Stadt Bern (1940): Bern und seine Entwicklung - graphisch-statistischer Atlas; Statistisches Jahrbuch der Stadt Bern, Bde. 1926-2002*".

Table 1.O.48. Final house price index for Bern

PERIOD	SOURCE	DESCRIPTION
1912-1933	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales within Bern from yearbooks; *Method*: Average price per transaction.
1933-1985	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: All sales aggregated by district from yearbooks; *Method*: Stratification.
1985-2018	*Wüest Partner*	*Type(s) of dwellings*: Single-family houses; *Type of data*: Private transaction-level data; *Method*: Hedonic index.

between 1890 and 1914 we instead had to rely on the rent index published by Curti (1981). We describe the two sources in more detail below.

Statistics Bern already started to calculate a rent index in 1914. They kindly provided the yearly rent index starting in 1940 directly to us. For the period between 1914 and 1940, we use the same index from one of their contemporaneous publications.[254] The index is calculated using a chained repeated rent approach. This means that the rent for the same dwellings is compared in two consecutive years. The statistical office adapts the rent changes on dwelling-level for major renovations. In 2018, approximately 2,000 rented dwellings were sampled and the number of missing values is below 5%. The repeated rents are weighted according to the share in the total stock of all rented dwellings to calculate the final index. We use November values from 1950 onward, May values between 1940 and 1950 and yearly values before 1940.

Prior to World War I, we use the rent index constructed by Curti (1981). Between 1890 and 1912, the author uses newspaper advertisements for three-room-apartments without a mansard in blue-collar worker districts. After 1912, he instead relies on aggregate rents published by Bern's housing office ("*städtisches Wohnungsamt*"). He again uses only three-room apartments, but this time pooled for apartments with and without a mansard and for the entire city. Next, he chains both indices and calculates three-year moving averages. The resulting index is used to interpolate between housing census data in 1896, 1913 and 1920 to build a final rent index, which matches the overall rent increase of the entire rented residential housing stock. We use this final index between 1890 and 1914.

Table 1.O.49 summarizes the components of our final rent index.

Rental Yield Series. As our main benchmark in 2018, we use the net rental yield from *MSCI* as described in the main paper. Applying the rent-price approach to this

254. "*Statistisches Jahrbuch der Stadt Bern*" (1940) p.106.

Table 1.O.49. Final rent index for Bern

PERIOD	SOURCE	DESCRIPTION
1890 - 1914	Curti (1981)	*Type(s) of dwellings*: Three-room apartments; *Type of data*: Newspapers, aggregate data from housing office; *Method*: Three-year moving average adjusted with housing census data in 1896, 1913 and 1920.
1914 - 2018	Statistics Bern	*Type(s) of dwellings*: All rented dwellings; *Type of data*: Micro-level sample of repeated rents; *Method*: Repeated rent index.

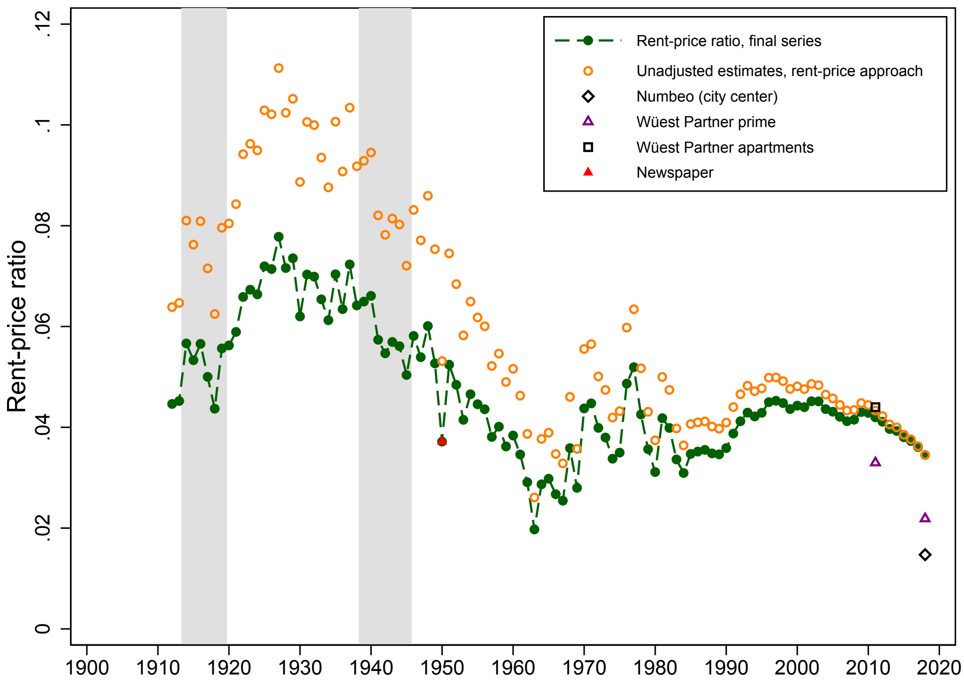

Figure 1.O.28. Bern: plausibility of rental yields

benchmark results in the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.28. We collected two additional benchmarks for 2018. First, we use the gross rental yield for the city-center of Bern from *Numbeo.com*. We adjust this benchmark to capture the net rental yield by subtracting one-third following Jordà et al. (2019). Second, we use the prime yield ("*Spitzenrendite*") for Bern published by *Wüest Partner* in their Swiss market reports.[255] It is calculated as

255. "*Immobilienmarkt Schweiz 2018|4*"

the net initial yield (net earnings/gross purchase price) for fully let prime properties at top locations. We adjust this yield for the vacancy rate in Bern given in the same publication. Both benchmarks are somewhat below our main benchmark from *MSCI*. We use the benchmark by *Wüest Partner* as our alternative benchmark in the robustness section of the main paper.

We additionally collected two types of historical benchmarks. First, we use the prime yield adjusted for the vacancy rate and the net-cash-flow yield ("*Netttocash-flowrendite*") for rental apartments published by *Wüest Partner* for 2011.[256] Our long-run series is again above the prime-yield, but very close to the net-cash-flow yield for apartments.

Second, we collected rental yield benchmarks from newspaper advertisements for the year 1950. We take the median rental yield adjusted for all costs by subtracting one-third as in Jordà et al. (2019). It proved to be hard to find newspaper advertisements that featured rental yields or price-rent ratios for properties in Bern, such that the sample size is very small. Considering the strict rent controls in Switzerland during this period,[257] the resulting values are still credible, as described above for Basel. The resulting net rental yield from the newspaper advertisements is with 3.72% again very close to the rate of 3.8% published in the rent policy report for Switzerland from 1950.

Like we did for Basel, we adjust our rental yield series to the newspaper benchmarks in 1950, because the strict rent controls until the 1960s probably bias our unadjusted rental yield series. The final rental yield series is plotted as the green-circled line in Figure 1.O.28.

1.O.13.3 Zurich

House Price Series. To construct the long-run house price index for Zurich, we use average sales prices of developed properties published by Statistics Zurich throughout. For the entire period, the data are disaggregated by county or even district. This allows us to control for sample shifts in the location of sold properties using stratification methods.

Starting in 1905, we use data by Statistics Zurich published in statistical yearbooks.[258] The yearbooks publish average prices of all voluntary sales of developed lots within Zurich.[259] Average prices are given disaggregated by 11 to 12 counties ("*Kreise*") and later on even by 34 statistical districts ("*statistische Quartiere*").[260]

256. Source: "*Wuest & Partner Immo-Monitoring 2012|2*" p. 173.
257. See e.g. the report "*Die Entwicklung des schweizerischen Mietrechts von 1911 bis zur Gegenwart*" by Helen Rohrbach (2014).
258. "*Statistisches Jahrbuch der Stadt Zürich*" (Volumes 1905-2017); after 2017, no statistical yearbook was published anymore, but Statistics Zurich kindly provided the necessary data.
259. "*Handänderungen von Freihandverkäufen bebauter Grundstücke*".
260. Until 1989, the counties 11 and 12 are aggregated in the data. This implies, that the number of counties is only 11 until 1989 and the number of statistical districts only 32, because county 12

We use the data by counties until 1984 and from there on the data by statistical district. Moreover, we use price per transaction instead of the price per square meter for the earlier period, because the price per square meter results in a noisier series. The reason seems to be that, during the earlier years, some agrarian developed lots ("*Landwirtschaftliche Bauten*") were sold in Zurich, as shown in the statistical yearbooks. These lots had abnormally large areas but low prices, such that the average price per square meter is biased and fluctuates with the number and size of these types of lots sold. As the number of these lots sold per year was very low in general, the average price per transaction is biased considerably less. In 1984, Zurich was already heavily urbanized and no agrarian lots were transacted anymore. This category is even excluded from the yearbooks from 1985 onward. Hence, using price per square meter arguably leads to a less biased series from then on, because it additionally controls for the size of developed lots that are sold. By switching to statistical district-level data, we also ensure that transacted properties within each stratum are even more similar over time. Moreover, the data on number of transactions are missing in the yearbooks from 1989 onward. For both sub-periods we build chained Fisher-type stratification indices following Eurostat (2013). When using price per transaction we use the number of transactions per stratum as weights and for price per square meter the total area transacted in square meters by stratum.

Table 1.O.50 summarizes the components of our final house price index.

Table 1.O.50. Final house price index for Zurich

PERIOD	SOURCE	DESCRIPTION
1905-1984	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: Price per transaction of all sales aggregated by counties from yearbooks; *Method*: Stratification.
1984-2018	Own compilation	*Type(s) of dwellings*: All developed lots; *Type of data*: Price per square meter of all sales aggregated by statistical district from yearbooks; *Method*: Stratification.

Rent Series. Our long-run rent index for Zurich is composed of the rent index produced by Statistics Zurich for nearly the entire time period. Only for the period between 1890 and 1914 we instead rely on the rent index published by Curti (1981). We describe the two sources in more detail below.

was counted as only one statistical district. Counties 9 to 11 are missing before 1934, because these counties were incorporated into Zurich in this year. When comparing 1933 to 1934, we therefore exclude these counties as well, such that only the same counties are compared for consecutive years.

Statistics Zurich already started to calculate a rent index in 1914. The data from 1940 onward are available on their website.[261] For the earlier period, we use the same index from one of their contemporaneous publications.[262] The index is calculated to construct a city-level CPI index. It measures rent developments for one to six room dwellings within the city of Zurich. For details about the methodology used please refer to Statistics Zurich. We use yearly averages for the monthly index throughout.

Prior to World War I, we use the rent index constructed by Curti (1981). Between 1890 and 1910, the author uses newspaper advertisements for three-room apartments without a mansard in blue-collar worker counties.[263] From 1908 to 1920, he additionally uses statistical data about dwellings advertised through a public institution.[264] He again uses only three-room apartments without a mansard in the same counties. The author chains both resulting indices. For the years the series overlap, Curti builds a weighted average of both indices. Next, he calculates three-year moving averages. The resulting yearly index is used to interpolate between housing census data in 1896, 1910 and 1920 to build a final rent index, which matches the overall rent increase of the entire rented residential housing stock. For details please refer to the aforementioned source. We use the final index between 1890 and 1914.

Table 1.O.51 summarizes the components of our final rent index.

Table 1.O.51. Final rent index for Zurich

PERIOD	SOURCE	DESCRIPTION
1890-1914	Curti (1981)	*Type(s) of dwellings*: three-room apartments; *Type of data*: Newspapers, statistical data about advertised dwellings; *Method*: three-year moving average adjusted with housing census data in 1896, 1910 and 1920.
1914-2018	Statistics Zurich	*Type(s) of dwellings*: Rented residential dwellings with 1-6 rooms; *Type of data*: From CPI index construction; *Method*: CPI rent index.

Rental Yield Series. As described in the main paper, we use the net rental yield from *MSCI* as our main benchmark in 2018. Applying the rent-price approach to this

261. "*Statistik Stadt Zürich*", "*Zürcher Index der Konsumentenpreise, Mietpreisindex*"; https://www.stadt-zuerich.ch/prd/de/index/statistik/themen/bauen-wohnen/mietpreise/mietpreisindex/mietpreisindex.html.
262. "*Statistisches Jahrbuch der Stadt Zürich*" (1950) p.67.
263. The author relies on advertisements in the later counties 3, 4, 5 and 6.
264. "*Der städtische Wohnungsnachweis*".

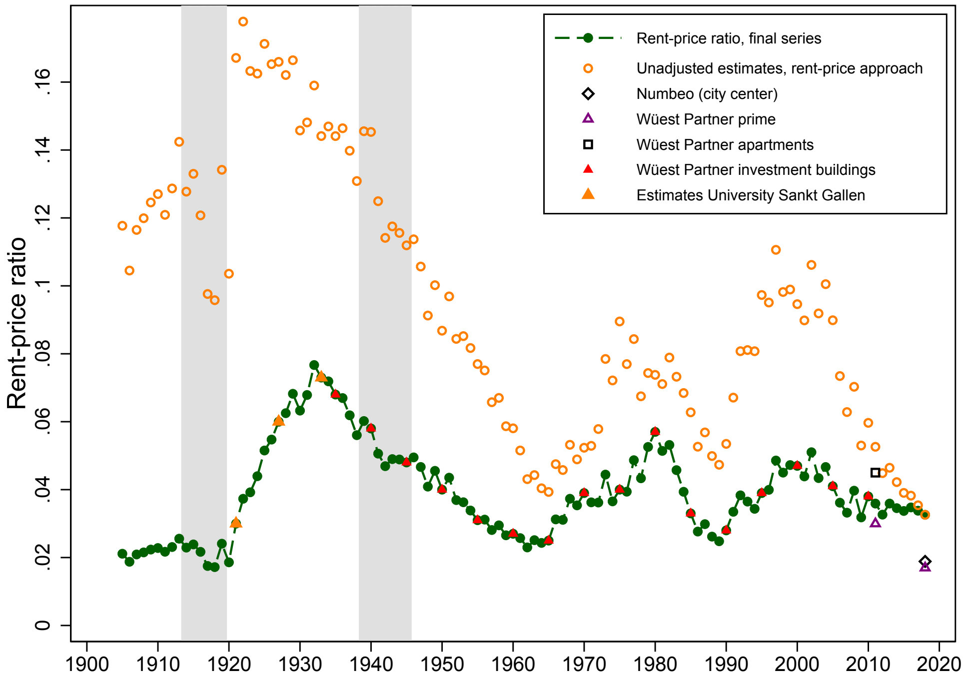

Figure 1.O.29. Zurich: plausibility of rental yields

benchmark results in the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.29. We collected two additional benchmarks for 2018. First, we use the gross rental yield for the city-center of Zurich from *Numbeo.com*. We adjust this benchmark to capture the net rental yield by subtracting one-third following Jordà et al. (2019). Second, we use the prime yield ("*Spitzenrendite*") for Zurich published by *Wüest Partner* in their Swiss market reports.[265] It is calculated as the net initial yield (net earnings/gross purchase price) for fully let prime properties in top locations. We adjust this yield for the vacancy rate given in the same publication. Both benchmarks are somewhat below our main benchmark from MSCI. Like for the other Swiss cities, we use the benchmark by *Wüest Partner* as our alternative benchmark in the robustness section of the main paper.

We additionally collected three types of historical benchmarks. First, we use the prime yield adjusted for the vacancy rate and the net-cash-flow yield ("*Netttocashflowrendite*") for rental apartments published by *Wüest Partner* for 2011.[266] Our long-run series is again above the prime-yield, but close to the net-cash-flow yield.

265. "Immobilienmarkt Schweiz 2018|4"
266. Source: "*Wuest & Partner Immo-Monitoring 2012|2*" p. 173.

Second, another chapter within same publication by *Wüest Partner* provides estimates of net-cash-flow yields ("*Netttocashflowrendite*") for residential investment buildings within the city of Zurich between 1931 and 2010.[267] To construct these estimates, *Wüest Partner* combined their transaction-level sales data with rent estimates calculated using data from Statistics Zurich. We collected rental yield benchmarks for five-year steps using these estimates. The benchmarks are plotted as red triangles in Figure 1.O.29. They show the same cyclical behavior as our unadjusted long-run series, but the values are considerably below our series.

Third, we collected net rental yield benchmarks for Zurich from a publication by the University of Sankt Gallen.[268] They estimate net rental yields of investment buildings for the years 1921, 1927 and 1933. These estimates are depicted as orange triangles in Figure 1.O.29. The resulting benchmarks are also considerably below our unadjusted long-run series.

As strict rent controls until the 1960s probably bias our unadjusted rental yield series and all historical benchmarks prior to 2011 are considerably lower compared to our series, we benchmark our series to all benchmarks prior to 2011. Especially the benchmarks for investment buildings by *Wüest Partner* seem to be more reliable compared to our series, because they use micro-level sales data to estimate net rental yields. Moreover, the estimates by *Wüest Partner* are in line with the earlier estimates by the University of Sankt Gallen. Hence, we infer that also the earlier estimates are more plausible compared to our unadjusted series. The final rental yield series is plotted as the green-circled line in Figure 1.O.29.

267. Source: "*Wuest & Partner Immo-Monitoring 2012|2*" chapter 5 p. 67.
268. "*Die Wohn- und Siedlungspolitik der Kantone und Gemeinden*", in "*Veröffentlichungen der Schweizerischen Verwaltungskurse an der Handels-Hochschule Sankt Gallen*", p.24.

1.0.14 United Kingdom

The five largest cities in the United Kingdom in 1900 were in descending order: London, Manchester, Birmingham, Glasgow and Liverpool. All of them encompassed more than one percent of the country population in 1900. However, to the best of our knowledge, no complete long-run data on either house prices or rents exists for any of these cities. Consistent house price data in the U.K. on the local planning authority level starts in 1974.[269] Consistent rent data only starts in 1997 for private registered providers and in 2010 for private market rents.[270] Before, we are only aware of city-level data for London. We use these data and compiled additional new series to construct housing return data for London.

1.0.14.1 London

House Price Series. A house price index is available for London from 1968 onward from the *HM Land Registry*. For later periods, there are also other indices available, for example from *Rightmove*, which uses asking prices, *Nationwide* or *Halifax*, which use their own mortgage approvals data. We rely on the *HM Land Registry* index for consistency and as it is based on a large sample using actual transaction prices (see below).[271] Before, there only exist a house price index between 1895 and 1939 from Samy (2015). To the best of our knowledge, there does not exist any house price index for London for other time periods. We therefore built a hedonic house price index for London for the intermediate period using newspaper advertisements.

The *HM Land Registry* publishes together with the *Office for National Statistics* (ONS) a house price index for London under the title *UK House Price Index* (UK HPI). The index is based on all residential real estate transactions collected as part of the official registration process that are sold for full market value. Using this micro-level data the ONS calculates a hedonic house price index. We use the index based on all property types for the London region, which is equivalent to the Greater London area. We use yearly averages of the monthly index.

Samy (2015) calculates hedonic house price indices using actual house price data from (1) the yearbooks of the *London Auction Mart* (1895-1922) and (2) the mortgage registers of the *Co-operative Permanent Building Society* (1919-1939). We use the double imputation chained fisher hedonic index presented in the paper. We use the index based on the Auction Mart data until 1922, because it has a larger sample size and focuses more on properties to let, such that it will be more comparable to the rent index.

269. See **Hilber2015**.
270. See Hilber and Mense (2021).
271. For a comparison of the indices, data and methods used please refer to the documentation of the UK House Price Index, for example here: https://www.gov.uk/government/publications/about-the-uk-house-price-index/comparing-house-price-indices-in-the-uk.

To fill the gap between the two indices, we use house asking price data from newspaper advertisements to calculate hedonic house price indices. We relied on digitized newspapers, which were available online, and focused on local newspapers as these covered a more standard market segment. Since the availability of the newspapers and the number of advertisements within each newspaper changed over time, we had to use three different newspapers. We collected advertisements for freeholds and leaseholds, which met the following three conditions: First, the advertisement contained information about the price (freehold or leasehold), the type of residence (house, flat...), some indicator of dwelling size (number of rooms or at least number of bedrooms) and the location. Second, we could match the location to a London borough (which we were able to do for nearly all advertisements we collected). Third, the leasehold period (if given) was at least 20 years. Applying these conditions we collected 522 observations from the *West London Observer* (WLO, 1946 - 1954), 3,163 observations from the *Norwood News* (NN, 1946 - 1962) and 521 observations from the *Kensignton Post* (KP, 1962 - 1969). We construct two different indices, one by pooling the advertisements from the first two newspapers together and one only using data from the KP, as the KP covers a significantly different market segment compared to the other two newspapers (unfortunately, data from the NN were not available after 1962). As we collected data for 1962 from both the NN and the KP, we are able to chain the indices. For both periods, we constructed five-year rolling-window time-dummy hedonic indices using a non-parametric approach,[272] because it best fits the trade-off between having enough observations to use a sufficient number of control variables still generating enough statistical power and the time flexibility of coefficients.[273] To construct the index we regressed the log house price on: year dummies; dummies for the total number of all normal rooms (bedrooms + lounges + receptions + sculleries or simply number of rooms if only totals are given); dummies for the number of bathrooms (if given, otherwise category 0 for missing); dummies for the number of kitchens (if given, otherwise category 0 for missing); a dummy for each London borough; a dummy for the house type (house, flat or maisonette); a separate dummy when the advertisement states the house has at least one garden, garage or is furnished; a dummy for leaseholds, an interaction term of the leasehold dummy and the leasehold period (if given and less than 100 years), a dummy for very long leaseholds (100+ years) and a dummy for leaseholds with a missing period.[274] We do not control for ground rent, as this information seems to be missing in most cases. If we include a control for ground rent, however, the resulting index is very similar.

272. We follow the methodology used in Keely and Lyons (2022).
273. This way, we only need to assume that coefficients of the hedonic regressions are stable for a period of five years, which might be much more realistic than assuming that coefficients were stable for the entire time period.
274. For the leasehold variables see also Samy (2015).

To link the final house price index for London from 1939 to 1946, we use the Land Registry Index described in Knoll, Schularick, and Steger (2017). According to the authors, the data used to construct the Land Registry Index have to a very large extent been collected from properties in the London area. Using this index, the house price series increases slightly less during World War II compared to the national series. This might, however, be realistic considering that real house prices did not fall in London in the late 1920s and early 1930s, but did decrease considerably during that period for the national house price index in Knoll, Schularick, and Steger (2017). As this index still covers properties outside London, we do not use it to impute the missing years during World War II, but only to link the indices before and afterwards.

Table 1.O.52. Final house price index for London

PERIOD	SOURCE	DESCRIPTION
1895-1939	Samy (2015)	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Micro-data from the London Auction Mart (1895-1922) and the mortgage registers of the Co-operative Permanent Building Society (1923 - 1939) ; *Method*: Hedonic index.
1946-1968	Own compilation	*Type(s) of dwellings*: Houses, flats or maisonettes; *Type of data*: Newspaper advertisements from the *West London Observer*, the *Norwood News* and the *Kensington Post*; *Method*: Hedonic index.
1968-2018	HM Land Registry	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Transaction-level data from the HM Land Registry; *Method*: Hedonic index.

Rent Series. Rent indices for London are available from Eichholtz, Korevaar, and Lindenthal (2019) for the period between 1870 and 1959 and from the *Office for National Statistics* (ONS) from 1997 onward. Apart from these periods, to the best of our knowledge, there only exists a rent series for private registered providers. As these companies face a legal rent ceiling,[275] we do not want to rely on these data to measure rent growth. Instead, we build hedonic rent indices for the period in between relying on advertisements from a range of different newspapers.

Eichholtz, Korevaar, and Lindenthal (2019) build a rent index for London between 1225 and 1959. We use this index from 1870 onward. Between 1870 and 1903, the authors build a repeat sales index using data from Clark (2002). From 1903 to 1909, the authors rely on the hedonic rent index in Samy (2015). Afterwards, they again build a repeat sales index using data on residential rent prices

275. See Hilber and Mense (2021).

from seal books from the archives of *Trafalgar House Developments Ltd*. For details, please refer to the aforementioned paper.

For the most recent period, we rely on two different rent indices for London compiled by the ONS. Between 1997 and 2005, we use an index compiled using data on regional private rent collected during construction of the consumer price index. The index was published in 2019 in response to an ad-hoc request and covers the London region. From 2005 onward, we use the *Index of Private Housing Rental Prices* for the London region. This index is based on administrative data from the *Valuation Office Agency*. For both indices, we use yearly averages of the monthly index values.

To fill the gap between 1959 and 1997, we collected rent data from newspaper advertisements. We had to rely on different newspapers over time, as most newspapers had only been digitized for specific time periods and not at all times published a sufficient number of housing rent advertisements. We tried to rely on local newspapers as much as possible. As different newspapers arguably covered different housing market segments, we construct separate rent indices for different periods: 1946 to 1962 using the *London Observer* and the *Norwood News*, 1962 to 1969 using the *Kensington Post*, 1966 to 1992 using *The Times* and 1989 to 1997 using the *Hammersmith & Shepherds Bush Gazette*.

From every newspaper we only included advertisements for rents that fulfilled the following three conditions: First, the advertisement contained information about the rent (or income), the type of the residence (house, flat, room, etc.), some indicator of dwelling size (number of rooms or at least number of bedrooms) and the location. Second, we could match the location to a London borough (which we were able to do for nearly all advertisements we collected). Third, the leasehold period (if given) was at least five years. Fourth, we exclude large apartment buildings (when the place had more than three bathrooms, more than two kitchens or more than ten rooms). For all aforementioned time periods, we constructed five-year rolling-window time-dummy hedonic indices using a non-parametric approach,[276] because it best fits the trade-off between having enough observations to use a sufficient number of control variables still generating enough statistical power and the time flexibility of coefficients.[277] To construct the hedonic index we regressed the log yearly rent on: year dummies; dummies for the total number of all normal rooms (bedrooms + lounges + receptions + sculleries or simply number of rooms if only totals were given); dummies for the number of bathrooms (if given, otherwise category 0 for missing); dummies for the number of kitchens (if given, otherwise category 0 for missing); a dummy for each London borough; a dummy for the house

276. We follow the methodology used in Keely and Lyons (2022).

277. This way, we only need to assume that coefficients of the hedonic regressions are stable for a period of five years, which might be much more realistic than assuming that coefficients were stable for the entire time period.

type (house, flat, room or maisonette); a separate dummy when the advertisement states the residence has at least one garden, garage or is furnished; and a separate dummy for whether the advertised residence was also for sale or lease. We do not control for ground rent, as this information seems to be missing in most cases and is less relevant for rents. If we include a control for ground rent, however, the index stays virtually the same.

For the period between 1946 and 1969, we use 219 observations from the *West London Observer* (WLO, 1946 - 1954), 1,742 observations from the *Norwood News* (NN, 1946 - 1962) and 1,176 observations from the *Kensington Post* (KP, 1962 - 1969). We construct two different indices, one pooling the advertisements from the first two newspapers and one with the data from the KP, as the KP covers a significantly different market segment compared to the other two newspapers (unfortunately, data from the NN was not available after 1962).

For the period between 1966 and 1992, we use rent data from advertisements out of the newspaper *The Times* to calculate a hedonic rent index. After 1972, we only collected data for flats, so that observations are more comparable over time.[278] Prior to 1972 we did not find enough observations to focus exclusively on flats.[279] Moreover, we exclude all duplicates and all very cheap[280] and very expensive[281] observations. After the data cleaning we were able to use 4,269 observations (1966-1992, with most between 1969 and 1989).[282]

For the period between 1989 and 1997, we use rent data from advertisements out of the newspaper *Hammersmith & Shepherds Bush Gazette*. We exclude all duplicates and two very expensive[283] observations. Afterwards, we could rely on 3,519 observations.

Table 1.O.53 summarizes the components of our final rent index. For the period between 1946 and 1959 we rely on the index by Eichholtz, Korevaar, and Lindenthal (2019), because it used actual rent data instead of asking prices and is based on a large number of observations. We only use the index we constructed using *The Times* from 1969 to 1989, as it arguably covers a special market segment and is based on fewer observations per year compared to the other newspaper indices for

278. As *The Times* was a supra-regional newspaper, housing advertisements sometimes covered luxurious or special real estate, which is less comparable over time. This problem is larger for houses, so that we focused on flats when possible. The other newspapers were local newspapers, which covered more comparable housing segments over time.
279. We, however, only use the index with all buildings constructed using *The Times* for three years between 1969 and 1972.
280. Below 100 pounds per year, mostly typos or not referring to residence.
281. Above 30,000 pounds per year, mostly especially luxurious flats, which are harder to compare over time.
282. There did not exist any data for 1982, so we have to interpolate this year - we use the rent component of the national CPI from Eichholtz, Korevaar, and Lindenthal (2019) for interpolation).
283. Above 50,000 pounds per year, large outliers.

the overlapping periods. As we collected data on overlapping years, we are able to chain the indices.

Table 1.O.53. Final rent index for London

PERIOD	SOURCE	DESCRIPTION
1870-1959	Eichholtz, Korevaar, and Lindenthal (2019)	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Micro-level data from various sources; *Method*: Repeat sales/hedonic index.
1959-1969	Own compilation	*Type(s) of dwellings*: Houses, flats, maisonettes or rooms; *Type of data*: Newspaper advertisements from the West London Observer, the Norwood News and the Kensington Post; *Method*: Hedonic index.
1969-1989	Own compilation	*Type(s) of dwellings*: Houses, flats, maisonettes or rooms; after 1972 only flats *Type of data*: Newspaper advertisements from the Times; *Method*: Hedonic index.
1989-1997	Own compilation	*Type(s) of dwellings*: Houses, flats, maisonettes or rooms; *Type of data*: Newspaper advertisements from the Hammersmith & Shepherds Bush Gazette; *Method*: Hedonic index.
1997-2005	ONS	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Data from CPI construction; *Method*: Stratification.
2005-2018	ONS	*Type(s) of dwellings*: All kinds of residential dwellings; *Type of data*: Administrative data from the Valuation Office Agency; *Method*: Stratification.

Rental Yield Series. Our main benchmark for London is taken from *MSCI*, as described in the main paper. This benchmark is reasonably close to the alternative benchmark collected from *Numbeo.com*, which we use in the robustness section of the main paper. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.30.

According to this series rental yields were unrealistically high in the pre-2000 period. The reason is that house prices and rents show fundamentally different trends after 1997. The rent series for London from ONS might, however, be mismeasured, because these are still experimental series and private market rents cover only a small market segment in London. As *MSCI* has extensive data coverage for London, we decided to instead rely on the MSCI-series for the period it is available, meaning for the years 1982-1984 and 1990-2018. Only for the period in between and before do we use the rent-price approach.

This gives us the adjusted final rent-price ratio series—the green-circled line in Figure 1.O.30.

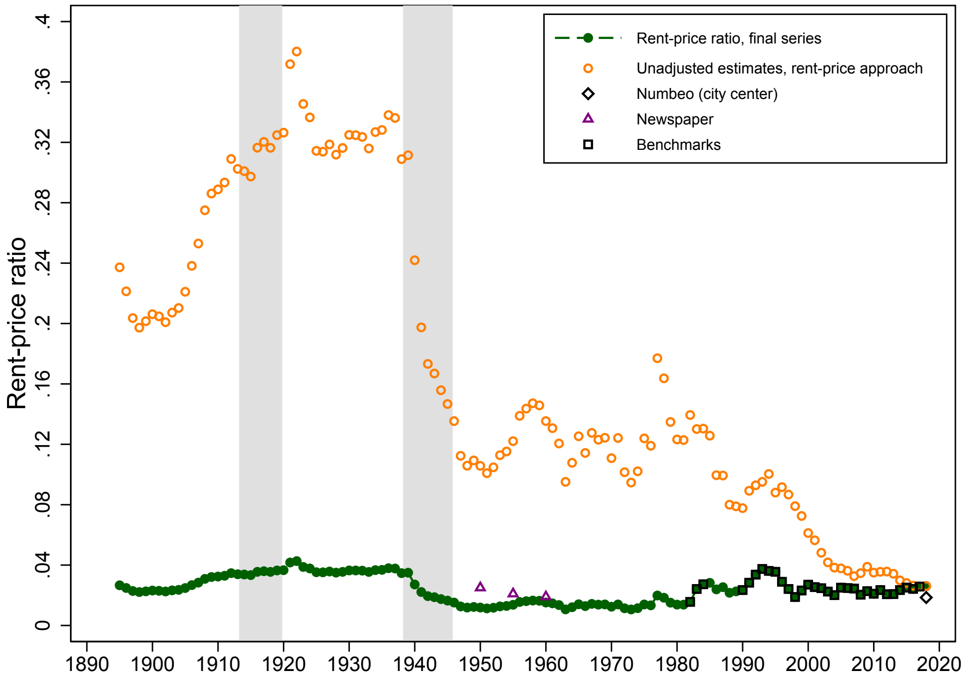

Figure 1.O.30. London: plausibility of rental yields

We collected additional benchmarks for gross rental yields from the newspaper data for 1950 (27 observations), 1955 (12 observations) and 1960 (8 observations). Following Jordà et al. (2019) we subtract one-third of these to get net rental yields. Median values are depicted in Figure 1.O.30. These values are reasonably close to our final rental yield series. As sellers have an incentive to overstate rental yields in newspaper advertisements, it does not come as a surprise that the benchmarks from the newspapers are somewhat above our series. For this reason and because benchmarks from newspapers are noisy as well, we do not adjust our rental yield series to these benchmarks.

1.O.15 United States

In 1900 the four largest cities in the United States were in descending order: New York City, Chicago, Philadelphia and Boston. All of these cities represented more than 1% of the national total population in 1900. New York was by far the largest, with almost 6% of the national population.

Although there exist housing series for the other three cities, they cover only specific historical periods in the twentieth century. Fishback and Kollmann (2014) use data from the Home Owners' Loan Corporation (HOLC) surveys, which they combine with census data, to build house price indices for the period between 1920 and 1940 for various different cities in the US. Unfortunately, for all these cities further house prices do not exist until the 1970s, when the Federal Housing Finance Association (FHFA) series start. For Chicago there is extensive literature on the long-run evolution of land values (Ahlfeldt and McMillen, 2018). However, to the best of our knowledge long-run series on house prices or returns do not exist. As such, we were able to construct a continuous long-run housing series only for New York.

1.O.15.1 New York

House Price Series. Nicholas and Scherbina (2012) built a house price index for Manhattan for the period between 1920 and 1939. The authors use 7,500 transaction prices from various issues of the publication *Real Estate Record and Builders' Guide*, alongside information on the characteristics of the properties transacted, to build a hedonic house price index. The data are mostly composed of transactions of multi-family houses, but also include apartment transactions. The hedonic indices control for type of dwelling (tenement, dwelling or loft), size (number of stories and square footage), location (neighborhood), construction material (brick, stone or other) and additional features (e.g. whether the property has a basement). The authors build a constant-relative-value hedonic index, which makes the assumption that the relative prices of the characteristics remain constant over time, and an adjacent-period hedonic index, which allows for time-varying prices of the characteristics. Since both indices produce very similar results we use the former for our long-run New York index.

For the period between 1940 and 1975 we use a house price index based on yearly median prices of multi-family houses (tenements) in Manhattan, which was published in Barr, Smith, and Kulkarni (2018). The transaction data were taken from the annual volumes published by the Real Estate Board of New York. Although the index does not control for quality adjustments over time, Barr, Smith, and Kulkarni (2018) show that it strongly correlates with a hedonic land value index of Manhattan in this period.

For the period after 1975 we rely on the house price county indices from the Federal Housing Finance Agency (FHFA) to create a house price index for the city of New York. The county indices are built using transaction and appraisals data on single-family house purchases and refinances from a mortgage transactions data set, which contains almost the whole universe of mortgages acquired or guaranteed by Fannie Mae or Freddie Mac. The index is based on a repeat-sales approach, which uses a weighted least squares (WLS) approach to handle heteroskedasticity due to constant differences between transactions with different holding periods. For more details about the index please refer to Bogin, Doerner, and Larson (2018). To construct the New York city-level index we use the house price indices for the following counties: Bronx, Kings, New York (Manhattan), Queens and Richmond. We aggregate the county-level indices by using a simple yearly average, since we did not have access to the volume of transactions at the county level.

To the best of our knowledge, there do not yet exist historical real estate indices for the city of New York covering the period between 1920 and 1975. By focusing on Manhattan, we think that we are still approximating the general house price evolution in New York relatively well, since Manhattan was throughout this period the most expensive part of New York and represented a large share of the housing transactions in the city of New York (Barr, Smith, and Kulkarni, 2018).

For the more recent period there are at least two additional indices for New York. The *S&P/Case-Shiller* index covers the Metropolitan Statistical Area (MSA) of New York since 1987 and the Zillow series on house values covers the city of New York since 1996. Zillow uses a hedonic approach to approximate the average value of residential housing in New York. To keep our geographical approach consistent over time, we decided not to use the index from *S&P/Case-Shiller*, which covers the complete MSA of New York. Additionally, we decided to use the FHFA indices, and not the housing values from Zillow, since the FHFA index covers a longer period of time and, as a result, reduces the number of different sources we are using.

Table 1.O.54 summarizes the components of our final house price index.

Table 1.O.54. Final house price index for New York

PERIOD	SOURCE	DESCRIPTION
1920-1939	Nicholas and Scherbina (2012)	*Type(s) of dwellings*: Multi-family houses and apartments ; *Type of data*: Transaction prices from Real Estate Record and Builders' Guide ; *Method*: Constant-relative-value hedonic index.
1940-1975	Barr, Smith, and Kulkarni (2018)	*Type(s) of dwellings*: Multi-family houses ; *Type of data*: Transaction prices from the Real Estate Board of New York; *Method*: Median price .
1975-2018	FHFA	*Type(s) of dwellings*: Single-family houses ; *Type of data*: Transaction prices and appraisals from FHFA mortgage data set; *Method*: Repeat-sales .

Rent Series. Our long-run rent series for New York is based on the residential rent component of the consumer price index (CPI) series constructed by the Bureau of Labour Statistics (BLS) for the MSA of New York for the period between 1914 and 2018. The residential rent component is based on data from the housing surveys conducted by the BLS on a frequent basis on a representative and rotating sample of households within the MSA. The rent series are quality-adjusted in the sense that extra charges or costs are taken into account to estimate the exact price change in rents. For a more detailed overview of the methods used please refer to Labour Statistics (2009).[284] We have two concerns about using the BLS series.

First, the series might under-estimate the impact of new rental contracts on the market, by focusing to a large extent on existing contracts.[285] This could create a wedge between our house price series, which is largely affected by new housing, and our rent series, which mostly relies on existing rental contracts. Second, the BLS series is meant to approximate the rent price growth in the New York MSA, while our house price series focuses on the city of New York.

To attenuate these concerns, we corrected the growth rates of the rental series from the BLS using the average rent values for the city of New York from the census for the years of 1950, 1960, 1970, 1980 and 1990. We do this by adjusting the BLS rent series for the growth in average rents in the city of New York using census data between 1950 and 1990. In Figure 1.O.31 we plot the original nominal rent series from BLS and the rent series we adjusted using the census data on average rents for New York. As expected, rent prices grew more in the city of New York than in the MSA of New York and the differences are quite significant over time. As a result, we use the adjusted rent series in our final rent series for New York. Table 1.O.55 summarizes the components of our final rent index.

As with house prices we are not aware of other historical quality-adjusted rental series for the city of New York. Since 2010 Zillow has published an average rental value for New York based on a hedonic approach using data on asking rents from online real estate ads. To keep a constant method over time, we decided not to use the rental values from Zillow, which nevertheless show a very similar trend for the overlapping years.

Rental Yield Series. Our main benchmark for New York is taken from *MSCI*, as described in the main paper. This benchmark is relatively high compared to the alternative benchmark we collected for 2018 from Demers and Eisfeldt (2021). According to Demers and Eisfeldt (2021) the net residential yield in the New York MSA in 2018 was 1.8%. However, our benchmark from *MSCI* is a bit lower than

284. Although the sampling and estimation methodologies of BLS have changed over time, the points made above have remained a consistent concern of the BLS.
285. A similar concern about the rent component of the CPI in European cities is raised in Eichholtz et al. (2020).

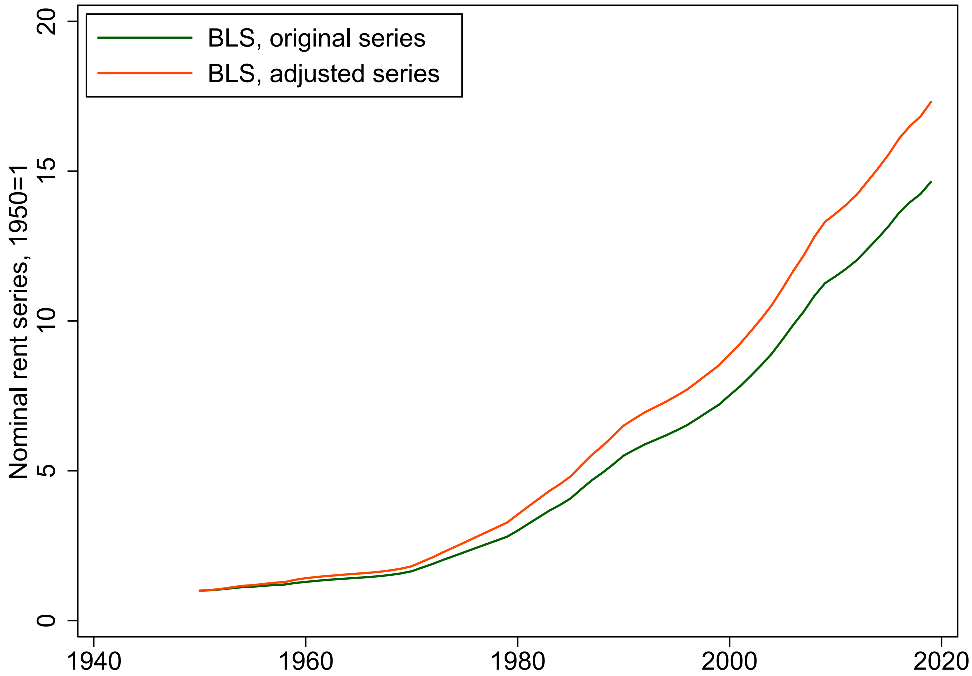

Figure 1.O.31. Nominal rent series for New York, 1950=1

Table 1.O.55. Final rent index for New York

PERIOD	SOURCE	DESCRIPTION
1914 - 2018	Own compilation	*Type(s) of dwellings*: Renter-occupied dwellings ; *Type of data*: Rental values from BLS housing surveys and census ; *Method*: Quality-adjusted rent series.

the benchmark from *Trulia.com* for 2018, which calculated the ratio of the median gross rent to median house price in the city of New York to be 0.0612. We then adjust for one-third costs to get an estimate of net yield of 4%. Applying the rent-price approach to our main benchmark gives us the unadjusted long-run net rental yield series depicted as orange circles in Figure 1.O.32.

Although we try to correct for geographical coverage differences in our rent and price series, there might still exist a wedge between the two series. This could lead to an under-estimation of the rent growth in the city of New York, since we are using the MSA-level rent series. In turn, this could bias our rental yield series upwards for the beginning of our sample. As a result we also collected a net yield benchmark from Demers and Eisfeldt (2021) for 1985. As can be seen from Figure 1.O.32 this benchmark lies substantially below our unadjusted series. As a result, we adjusted

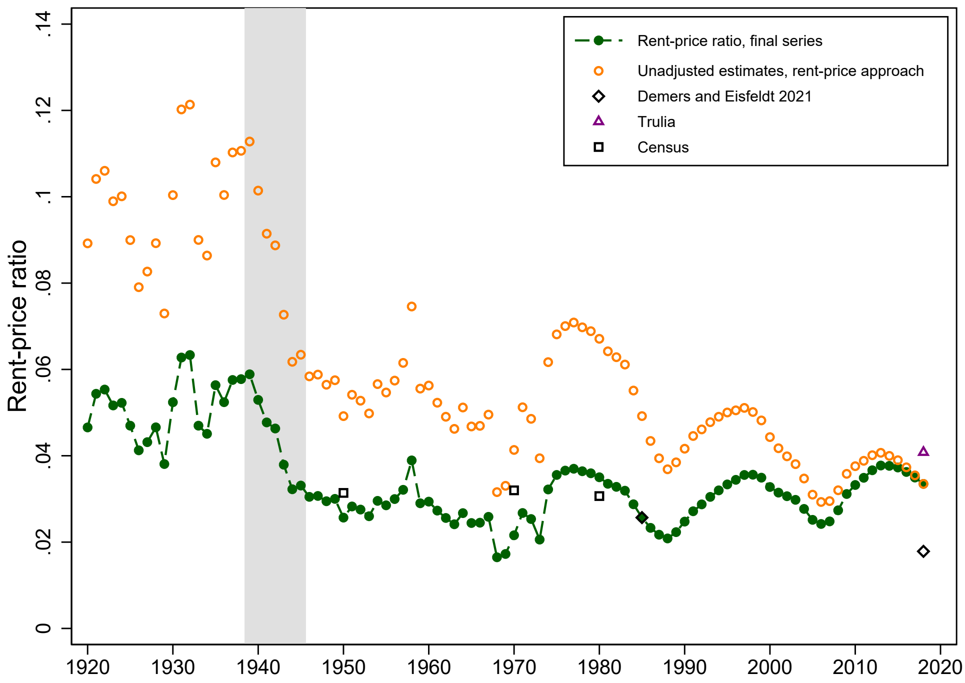

Figure 1.O.32. New York: plausibility of rental yields

our series to the benchmark. This gives us the adjusted final rental yield series—the green-circled line in Figure 1.O.32.

Additionally, we also build historical benchmarks using census data on mean house value and mean rent paid for the years 1950, 1970 and 1980.[286] We then adjust these estimates assuming one-third costs. As can be seen in Figure 1.O.32 these benchmarks lie below our unadjusted series, but very close to our adjusted series.

To the best of our knowledge, there do not exist reliable estimates of rent-price ratios for New York for the period before 1950. As a result, we cannot be sure that our estimated rental yield series is correct for this period. However, a study by Grebler (1955) using data on income properties in Manhattan shows that multi-family houses yielded a net rental income of about 9% in the second half of the 1920s, and a net rental income of 3.5% in the 1930s and 1940s.[287] The strong volatility in the estimates provided by the author question its accuracy. Since relatively few details are given about the methods, we do not use his estimates. Nevertheless, his data

286. Unfortunately, housing data for New York City are missing in the census of 1960.
287. The author collected data on rental income and expenses from the Real Estate Record and Builders' Guide.

seem to show a downward trend between 1930 and 1950, which our final series also reproduces.

Appendix 1.P Net Yields

Figure 1.P.1 displays operating costs as % of gross income for 22 different U.S. cities in 2007 and 2022. The data is from MSCI and operating costs are defined as Utilities, Maintenance, Property Taxes, Management Costs and Other Costs net of recoveries from tenants, plus Cost of Vacancies, Letting & Rent Review fees, Ground Rents, Bad Debt Write-offs, minus Unallocated Recovered Costs. The Figure does not reveal any systematic difference between large and small cities and also not over time.

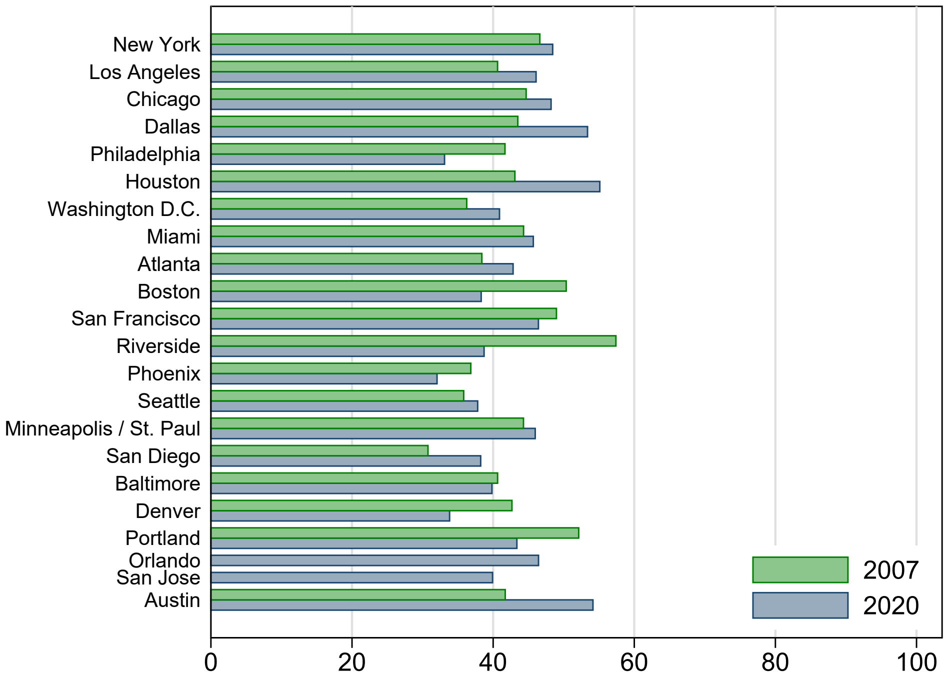

Figure 1.P.1. Operating costs as % of gross income, USA

Note: Data from MSCI. Operating costs are defined as: Utilities, Maintenance, Property Taxes, Management Costs and Other Costs net of recoveries from tenants, plus Cost of Vacancies, Letting & Rent Review fees, Ground Rents, Bad Debt Write-offs, minus Unallocated Recovered Costs.

Appendix 1.Q Log returns

Throughout the paper and in contrast to Jordà et al. (2019), we measure housing returns and their components in log points instead of simple (percentage) returns. This means we measure housing total returns as:

$$\text{Total return}_t \quad = \quad ln\left(\frac{P_t + R_t}{P_{t-1}}\right), \tag{1.Q.1}$$

and their components accordingly. This is a commonly used procedure in finance literature and frequently preferred to simple (percentage) returns for a variety of reasons.[288] In the following, we will discuss why we decided to use log returns throughout this paper, although this might complicate comparison to some other studies of housing returns.

Although simple returns and log returns are approximately equal for small numbers,[289] they have significantly different features. The most important one for our application is that simple returns aggregate linearly across securities, whereas log returns aggregate linearly across time (Meucci, 2010). Throughout this study, we mainly aggregate returns for various housing portfolios over time and compare these aggregates across space. Therefore, time additivity of returns is the more relevant feature in our application.

This feature is especially important when comparing average returns between city-level and national housing portfolios. Time additivity in this case implies that differences in the variance of returns across time do not bias our comparison. To see the contrast to simple returns, consider the following example: In city A, house prices increased by 50% in period 1 and fell by 1/3 in period 2, in city B house prices stayed constant. Using simple returns, average capital gains in city A are approximately 8.3% per year, but zero in city B. In fact, after two periods, prices in both cities are the same as in the very beginning and an investor holding a house for both periods realized a capital gain of zero. Using log returns, average capital gains for both example cities are indeed zero. As national housing portfolios are more diversified compared to city-level portfolios, their variance will typically be lower. Therefore, using simple returns would bias the comparison of city-level and national portfolios towards finding higher returns for city-level portfolios, although the returns over longer periods might not be favorable, just because we measure returns yearly and average them over time. The same bias might occur when comparing large to smaller cities. To be able to make unbiased comparisons, log returns are crucial in our study.

Apart from time additivity, log returns have other preferable features. First, log returns of securities are assumed to be normally distributed. This is true if security prices follow geometric Brownian motion, which is the stochastic process usually assumed for stock prices and the basis of the Black-Scholes-Merton model (Hull (2019), p. 316). Figure 2 in the paper suggests that log total housing returns are indeed close to be normally distributed. Even if the assumption of normally distributed log returns is violated, time additivity of log returns together with the central limit theorem ensure that compounded log returns converge to normality. Normal distri-

288. See Hudson and Gregoriou (2015).
289. For returns that are smaller than 0.15, log and simple returns are very similar in size (Hudson and Gregoriou, 2015).

bution of log returns is an important assumption for the estimation techniques used throughout our paper.

Other arguments for using log returns incorporate numerical stability and reduction of algorithmic complexity.[290] But there are also disadvantages of using log returns instead of simple returns.[291] In our application, using log returns implies that total returns are not equal to the simple sum of capital gains and rent returns. Moreover, and as stated above, log returns do not aggregate linearly across securities. Therefore, in the occasions in which we need to aggregate security returns, for example to calculate rest of country returns, we use simple returns and transform them to log returns only afterwards, but before time aggregation.

Appendix 1.R Summary statistics

Table 1.R.1. Summary of main statistics of US cities by decile

Statistic	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Mean Capital Gains	1.8216014	1.5862964	1.5671438	1.4172230	1.3897859	1.5008069	1.3323480	1.4321084	1.4738598	1.7164541
Mean Housing Return	5.6981678	5.4602585	5.4406734	5.5526428	5.4665761	5.4054842	5.2627072	5.3685255	5.2518086	5.0632787
Mean Income Growth	0.1445050	0.1436025	0.1455991	0.1363572	0.1298990	0.1357805	0.1304450	0.1348174	0.1373096	0.1439510
Mean Rental Yield	3.9470825	3.9331350	3.9323766	4.1914430	4.1310992	3.9608953	3.9804342	3.9901886	3.8316441	3.4003093
SD Capital Gains	2.1392958	1.6703887	1.8383975	1.6324029	1.7226529	1.8963023	1.6370192	1.7061670	1.6205136	1.8983406
SD Housing Return	2.2918999	1.7309659	1.9054415	1.6691561	1.7942142	1.8701003	1.6528352	1.7900476	1.7073641	1.9216055
SD Income Growth	0.1589575	0.1605740	0.1504481	0.1558239	0.1558202	0.1567641	0.1536207	0.1576912	0.1608882	0.1682487
SD Rental Yield	0.6276312	0.5428352	0.5702046	0.4937519	0.5297492	0.5814317	0.4356557	0.5469573	0.4990252	0.5677253

Note: The table shows the mean and standard deviation of the capital gains, yields, housing returns and income growth for the US-city sample by city-size deciles.

290. For a good summary please refer to https://quantivity.wordpress.com/2011/02/21/why-log-returns/.
291. For a more critical view on using log returns, refer for example to Hudson and Gregoriou (2015).

Table 1.R.2. Summary statistics on city-level housing returns (log points)

City	Full sample			Post 1950		
	Capital gain	Rent return	Total return	Capital gain	Rent return	Total return
London	1.50 (9.65)	2.52 (0.87)	3.99 (9.54)	3.21 (10.61)	2.14 (0.71)	5.27 (10.66)
New York	1.45 (12.25)	3.52 (0.98)	4.93 (12.08)	1.39 (12.36)	3.06 (0.55)	4.41 (12.19)
Paris	0.62 (11.20)	4.12 (0.98)	4.73 (10.95)	4.85 (9.14)	3.66 (1.12)	8.33 (9.17)
Berlin	1.08 (18.53)	4.77 (2.27)	5.78 (12.00)	3.51 (10.44)	5.68 (2.14)	9.00 (10.26)
Tokyo	2.01 (16.51)	5.24 (2.01)	7.17 (15.95)	2.01 (16.51)	5.24 (2.01)	7.17 (15.95)
Hamburg	1.09 (24.73)	4.29 (1.46)	5.32 (10.22)	2.12 (6.47)	3.45 (0.80)	5.52 (6.17)
Naples	1.35 (9.02)	3.28 (1.08)	4.58 (8.99)	1.35 (9.09)	3.32 (1.05)	4.62 (9.06)
Barcelona	1.74 (15.27)	3.91 (1.32)	5.58 (15.04)	1.74 (15.27)	3.91 (1.32)	5.58 (15.04)
Madrid	1.76 (16.86)	3.68 (1.06)	5.37 (16.63)	1.76 (16.86)	3.68 (1.06)	5.37 (16.63)
Amsterdam	1.10 (7.73)	5.96 (1.41)	7.02 (7.36)	2.80 (9.46)	5.65 (1.77)	8.32 (9.19)
Milan	3.77 (13.59)	1.85 (0.81)	5.53 (13.62)	3.44 (13.41)	1.83 (0.81)	5.19 (13.43)
Melbourne	2.11 (10.67)	4.33 (2.34)	6.39 (10.45)	2.52 (7.93)	2.54 (0.98)	5.00 (7.85)
Sydney	2.18 (9.91)	4.93 (2.52)	7.04 (9.69)	2.87 (8.22)	2.93 (1.03)	5.72 (8.15)
Copenhagen	2.59 (8.99)	2.28 (1.11)	4.82 (8.92)	2.86 (8.80)	1.92 (0.67)	4.72 (8.87)
Rome	1.64 (8.70)	1.10 (0.38)	2.73 (8.63)	1.22 (8.03)	1.11 (0.38)	2.32 (8.00)
Cologne	0.14 (32.82)	3.43 (1.13)	3.56 (15.32)	2.93 (10.66)	3.86 (0.76)	6.68 (10.50)
Frankfurt	0.21 (23.04)	5.16 (2.92)	5.38 (16.70)	3.65 (13.88)	4.46 (1.97)	7.93 (13.85)
Turin	1.00 (7.08)	2.78 (1.15)	3.74 (7.13)	0.98 (7.13)	2.81 (1.12)	3.76 (7.18)
Stockholm	0.93 (8.67)	3.60 (1.03)	4.50 (8.48)	1.93 (8.48)	3.90 (1.08)	5.76 (8.25)
Oslo	0.90 (13.35)	2.97 (0.74)	3.84 (13.18)	2.21 (10.14)	3.28 (0.81)	5.42 (9.98)
Toronto	1.67 (8.69)	5.53 (2.31)	7.10 (8.84)	1.82 (8.06)	4.18 (0.69)	5.92 (8.08)
Zurich	1.71 (12.17)	4.01 (1.32)	5.65 (12.10)	2.35 (12.22)	3.77 (0.77)	6.05 (11.93)
Gothenburg	1.33 (9.67)	6.29 (1.62)	7.55 (9.47)	2.12 (9.37)	5.91 (1.58)	7.93 (8.98)
Basel	1.67 (11.30)	4.04 (0.57)	5.65 (11.09)	2.67 (10.60)	3.96 (0.57)	6.53 (10.37)
Helsinki	3.26 (10.64)	4.17 (3.02)	7.29 (10.97)	3.59 (10.58)	3.62 (2.03)	7.04 (11.04)
Vancouver	2.80 (11.37)	3.95 (0.81)	6.62 (11.38)	2.80 (11.37)	3.95 (0.81)	6.62 (11.38)
Bern	0.98 (13.63)	4.70 (1.19)	5.65 (13.33)	1.31 (13.80)	3.97 (0.57)	5.23 (13.54)
Global mean	1.45 (14.85)	4.07 (1.97)	5.47 (11.61)	2.44 (11.00)	3.62 (1.64)	5.98 (10.94)

Note: The table shows arithmetic means of log returns for every city in our sample. Standard deviations are in parentheses. Returns are split up into capital gains and rent returns, log returns are calculated for each category separately. The full sample time period is city specific and refers to the minimum coverage of price and rent data by city depicted in Table 1 of the paper. The post-1950 period covers the same time period per city including return data from 1951 to 2018, except for some German cities, for which the first years after World War II are missing due to data availability.

Appendix 1.S National housing data

Table 1.S.1 shows the geographical coverage of the national house price series used by Jordà et al. (2019) and constructed by Knoll, Schularick, and Steger (2017), except for two adaptions (cf. see below). For recent years, the series for most countries have nationwide coverage or cover at least the majority of urban areas. Going further back, however, geographical coverage becomes somewhat narrower and is even reduced to one or two large cities for some countries. Therefore, in our main analysis we only use the national series post-1950.

National rent series from Jordà et al. (2019) typically have a broad coverage, as they are taken from national CPIs, which are constructed to be representative on

Table 1.R.3. Summary statistics on city-level simple housing returns (percentage points)

City	Full sample Capital gain	Rent return	Total return	Post 1950 Capital gain	Rent return	Total return
London	2.22 (9.71)	2.54 (0.88)	4.76 (9.80)	3.84 (11.07)	2.16 (0.72)	6.00 (11.32)
New York	2.21 (12.43)	3.59 (1.01)	5.80 (12.64)	2.16 (12.71)	3.11 (0.56)	5.27 (12.85)
Paris	1.24 (10.95)	4.22 (1.02)	5.45 (11.18)	5.41 (9.93)	3.74 (1.17)	9.15 (10.37)
Berlin	1.79 (12.00)	4.91 (2.41)	6.70 (12.70)	4.12 (10.84)	5.87 (2.29)	9.99 (11.32)
Tokyo	3.36 (16.60)	5.40 (2.14)	8.76 (17.04)	3.36 (16.60)	5.40 (2.14)	8.76 (17.04)
Hamburg	1.62 (10.55)	4.39 (1.53)	6.01 (11.06)	2.36 (6.78)	3.51 (0.83)	5.87 (6.66)
Naples	1.78 (9.63)	3.34 (1.12)	5.12 (9.91)	1.78 (9.70)	3.38 (1.09)	5.16 (9.98)
Barcelona	2.90 (15.49)	3.99 (1.37)	6.90 (15.83)	2.90 (15.49)	3.99 (1.37)	6.90 (15.83)
Madrid	3.23 (17.87)	3.75 (1.11)	6.98 (18.32)	3.23 (17.87)	3.75 (1.11)	6.98 (18.32)
Amsterdam	1.40 (7.75)	6.15 (1.49)	7.55 (7.84)	3.28 (9.41)	5.83 (1.87)	9.12 (9.73)
Milan	4.82 (14.97)	1.87 (0.83)	6.68 (15.26)	4.45 (14.76)	1.85 (0.82)	6.30 (15.04)
Melbourne	2.82 (14.55)	4.46 (2.45)	7.28 (14.69)	2.87 (8.13)	2.57 (1.00)	5.44 (8.23)
Sydney	2.74 (11.62)	5.09 (2.65)	7.83 (11.87)	3.25 (8.58)	2.98 (1.06)	6.23 (8.75)
Copenhagen	3.04 (9.15)	2.31 (1.14)	5.35 (9.28)	3.29 (9.02)	1.94 (0.68)	5.23 (9.22)
Rome	2.05 (9.29)	1.11 (0.38)	3.16 (9.31)	1.56 (8.44)	1.12 (0.38)	2.68 (8.49)
Cologne	1.27 (14.62)	3.50 (1.17)	4.77 (15.02)	3.57 (11.52)	3.94 (0.78)	7.51 (11.70)
Frankfurt	1.56 (15.93)	5.34 (3.12)	6.90 (16.52)	4.67 (14.08)	4.58 (2.11)	9.25 (14.64)
Turin	1.26 (7.40)	2.82 (1.18)	4.08 (7.63)	1.25 (7.45)	2.86 (1.16)	4.10 (7.68)
Stockholm	1.31 (8.54)	3.67 (1.08)	4.97 (8.72)	2.30 (8.53)	3.98 (1.13)	6.29 (8.68)
Oslo	1.77 (13.07)	3.01 (0.77)	4.79 (13.27)	2.74 (10.17)	3.34 (0.84)	6.08 (10.34)
Toronto	2.07 (9.22)	5.71 (2.48)	7.78 (9.92)	2.17 (8.52)	4.27 (0.72)	6.44 (8.87)
Zurich	2.47 (12.32)	4.10 (1.37)	6.57 (12.65)	3.12 (12.36)	3.85 (0.80)	6.97 (12.53)
Gothenburg	1.79 (9.28)	6.51 (1.73)	8.30 (9.72)	2.56 (8.92)	6.10 (1.69)	8.66 (9.16)
Basel	2.32 (11.49)	4.13 (0.59)	6.45 (11.69)	3.27 (10.96)	4.04 (0.59)	7.31 (11.08)
Helsinki	3.34 (12.12)	4.45 (3.46)	7.80 (12.60)	4.23 (11.19)	3.71 (2.15)	7.95 (12.26)
Vancouver	3.50 (12.02)	4.03 (0.84)	7.53 (12.45)	3.50 (12.02)	4.03 (0.84)	7.53 (12.45)
Bern	1.91 (13.62)	4.82 (1.25)	6.73 (13.85)	2.24 (13.52)	4.05 (0.60)	6.29 (13.69)
Global mean	2.15 (12.02)	4.18 (2.09)	6.32 (12.39)	3.09 (11.37)	3.70 (1.72)	6.80 (11.74)

Note: The table shows arithmetic means of simple (percentage point) returns for every city in our sample. Standard deviations are in parentheses. Returns are split up into capital gains and rent returns, simple returns are calculated for each category separately. The full sample time period is city specific and refers to the minimum coverage of price and rent data by city depicted in Table 1 of the paper. The post-1950 period covers the same time period per city including return data from 1951 to 2018, except for some German cities, for which the first years after World War II are missing due to data availability.

a national level. For cases when nationwide coverage was not possible, the authors tried to match geographical coverage of the house price series. For details please refer to Jordà et al. (2019).

We adapted the housing series of Jordà et al. (2019) only in two cases. First, we replaced the house price series for Japan from 2008 onward, because a series with a broader coverage and preferable methodology became available. The national house price series we use is produced by the *Ministry of Land, Infrastructure, Transport and Tourism* of Japan (https://www.mlit.go.jp/en/) using individual transaction-level data on detached houses and condominiums from the Land Registry of Japan. It covers all of Japan and uses the hedonic time-dummy variable approach. For more detail, please refer to the given source.

Table 1.S.1. Coverage of national house price series

Country	Period	Coverage
Australia	1870 - 1899	Melbourne
Australia	1900 - 2002	6 capital cities
Australia	2003 - 2018	8 capital cities
Canada	1921 - 1981	nationwide
Canada	1981 - 2018	27 metropolitan areas
Switzerland	1901 - 1929	Zurich
Switzerland	1930 - 1969	urban areas
Switzerland	1970 - 2018	nationwide
Germany	1870 - 1902	Berlin
Germany	1903 - 1923	Hamburg
Germany	1924 - 1938	10 cities
Germany	1939 - 1970	nationwide (Western Germany)
Germany	1971 - 2012	urban areas (Western Germany)
Germany	2013 - 2018	nationwide
Finland	1905 - 1969	Helsinki
Finland	1970 - 2018	nationwide
France	1870 - 1935	Paris
France	1936 - 2018	nationwide
United Kingdom	1899 - 1929	3 cities
United Kingdom	1930 - 1995	nationwide
United Kingdom	1995 - 2012	nationwide (England and Wales)
United Kingdom	2013 - 2018	nationwide
Italy	1927 - 1941	nationwide
Italy	1942 - 1966	8 cities
Italy	1966 - 1997	provincial capitals
Italy	1998 - 2018	nationwide
Japan	1913 - 1930	Tokyo
Japan	1931 - 1935	Kanto district
Japan	1936 - 2007	urban areas
Japan	2008 - 2018	nationwide
Netherlands	1870 - 1969	Amsterdam
Netherlands	1970 - 2018	nationwide
Norway	1870 - 2012	4 cities
Norway	2013 - 2018	nationwide
Sweden	1875 - 1952	Stockholm and Gothenburg
Sweden	1952 - 2018	nationwide
United States	1890 - 1928	22 cities
United States	1929 - 1940	106 cities
United States	1941 - 1952	5 cities
United States	1953 - 2018	nationwide

Second, we adapt the national house price series for Sweden between 1952 and 2018, because the series used in Jordà et al. (2019) had limited geographical coverage. We use three different sources, which are all in turn based on Statistics Sweden and very similar for overlapping periods. For the period after 1970, we rely on the nominal national house price index in the OECD analytical house prices indicators database. Between 1957 and 1970, we use the national series in Edvinsson, Blöndal, and Söderberg (2014) and before, we use the series kindly provided directly by Statistics Sweden. The OECD, in turn, uses the index of “Residential property prices, all owner-occupied houses, per dwelling, NSA" from Statistics Sweden from 1985 onward. Before this, all of our sources use the indices on “owner-occupied one- and two-dwelling buildings”, also constructed by Statistics Sweden. All series are constructed using the SPAR-method and cover almost the entire universe of real estate transactions in Sweden. They are based on all transfers of real-estate properties that are registered in the Land Survey of Property Prices (LSPP).

As we replace the national house price indices for both countries, we also recalculate rental yields, rent returns, capital gains and housing returns using the methodology of Jordà et al. (2019).

Additionally, we added a new national housing return series for Canada from 1956 to 2018. House prices are taken from the Canadian Real Estate Association between 1956 and 1981. The series contains annual data on the average value and the number of transactions recorded in the Canadian Multiple Listing System (MLS) for all properties, i.e. it includes both residential and non-residential real estate, therefore has nationwide coverage, and is also used in Knoll, Schularick, and Steger (2017) between 1956 and 1974. Afterwards, we deviate from the aforementioned authors and use a house price series from Statistics Canada between 1981 and 2018. The index is computed from sales prices of new real estate constructed by contractors based on a survey that is conducted in 27 metropolitan areas with the number of builders in the sample representing at least 15 percent of the total building permit value of the respective city and year. The construction firms covered mainly develop single-unit houses. The index is a matched-model index, i.e. a constant-quality index in the sense that the characteristics of the structures and the lots are identical between successive periods. For details, please refer to Statistics Canada. We prefer the index to the one used in Knoll, Schularick, and Steger (2017), because it has wider geographical coverage. For rents, we entirely rely on the rent component of the national CPI constructed by Statistics Canada.

As stated in the paper, we also updated the series from Jordà et al. (2019) to 2018. To update house price series, we solely relied on the nominal national house price indices in the OECD analytical house prices indicators database. To update rental series, we mainly relied on the respective national statistical agencies and used nominal national rent indices mostly constructed as part of the CPI series. Exceptions are Portugal and the U.S, for which we got the same kind of data from the FRED database. Many of these sources are already used in Jordà et al. (2019) for recent years. We calculate real series using CPI indices in the JST-database updated with series from the IMF World Economic Outlook database or national statistical agencies. With these series at hand, we calculate returns forward using the approaches described by the aforementioned authors. For rental yields, we use the rent-price approach to calculate rental yields forward coming from the series of Jordà et al. (2019).

1.S.1 Alternative rental yield benchmarks

Table 1.S.2. Summary statistics on returns in log points using alternative benchmarks

City	Full sample			Post 1950		
	Capital gain	Rent return	Total return	Capital gain	Rent return	Total return
London	1.50 (9.65)	2.50 (0.90)	3.97 (9.56)	3.21 (10.61)	2.11 (0.75)	5.23 (10.70)
New York	1.45 (12.25)	3.20 (1.16)	4.62 (12.07)	1.39 (12.36)	2.60 (0.60)	3.96 (12.16)
Paris	0.62 (11.20)	3.91 (1.17)	4.52 (10.91)	4.85 (9.14)	3.20 (1.27)	7.89 (9.27)
Berlin	1.08 (18.53)	4.28 (2.04)	5.29 (11.97)	3.51 (10.44)	5.09 (1.93)	8.44 (10.26)
Tokyo	2.01 (16.51)	4.69 (2.10)	6.62 (16.06)	2.01 (16.51)	4.69 (2.10)	6.62 (16.06)
Hamburg	1.09 (24.73)	4.28 (1.47)	5.31 (10.22)	2.12 (6.47)	3.43 (0.79)	5.49 (6.16)
Naples	1.35 (9.02)	3.28 (1.08)	4.58 (8.99)	1.35 (9.09)	3.32 (1.05)	4.62 (9.06)
Barcelona	1.74 (15.27)	3.58 (1.40)	5.26 (15.05)	1.74 (15.27)	3.58 (1.40)	5.26 (15.05)
Madrid	1.76 (16.86)	3.61 (1.09)	5.30 (16.64)	1.76 (16.86)	3.61 (1.09)	5.30 (16.64)
Amsterdam	1.10 (7.73)	6.10 (1.30)	7.14 (7.41)	2.80 (9.46)	5.95 (1.61)	8.60 (9.23)
Milan	3.77 (13.59)	3.11 (1.36)	6.74 (13.66)	3.44 (13.41)	3.09 (1.35)	6.40 (13.46)
Melbourne	2.11 (10.67)	4.33 (2.34)	6.39 (10.45)	2.52 (7.93)	2.54 (0.98)	5.00 (7.85)
Sydney	2.18 (9.91)	4.93 (2.52)	7.04 (9.69)	2.87 (8.22)	2.93 (1.03)	5.72 (8.15)
Copenhagen	2.59 (8.99)	2.90 (0.97)	5.42 (8.95)	2.86 (8.80)	2.65 (0.75)	5.42 (8.91)
Rome	1.64 (8.70)	2.27 (0.77)	3.88 (8.58)	1.22 (8.03)	2.29 (0.77)	3.49 (7.97)
Cologne	0.14 (32.82)	2.72 (0.90)	2.85 (15.35)	2.93 (10.66)	3.05 (0.60)	5.90 (10.53)
Frankfurt	0.21 (23.04)	4.58 (2.60)	4.80 (16.71)	3.65 (13.88)	3.95 (1.76)	7.45 (13.84)
Turin	1.00 (7.08)	2.78 (1.15)	3.74 (7.13)	0.98 (7.13)	2.81 (1.12)	3.76 (7.18)
Stockholm	0.93 (8.67)	2.69 (0.78)	3.60 (8.52)	1.93 (8.48)	2.91 (0.81)	4.79 (8.29)
Oslo	0.90 (13.35)	2.97 (0.74)	3.84 (13.18)	2.21 (10.14)	3.28 (0.81)	5.42 (9.98)
Toronto	1.82 (8.06)	3.56 (0.59)	5.32 (8.08)	1.82 (8.06)	3.56 (0.59)	5.32 (8.08)
Zurich	1.71 (12.17)	3.93 (1.37)	5.58 (12.07)	2.35 (12.22)	3.65 (0.88)	5.93 (11.89)
Gothenburg	1.33 (9.67)	4.03 (1.05)	5.31 (9.51)	2.12 (9.37)	3.78 (1.02)	5.84 (9.08)
Basel	1.67 (11.30)	3.52 (0.71)	5.13 (11.10)	2.67 (10.60)	3.15 (0.48)	5.73 (10.44)
Helsinki	3.26 (10.64)	4.17 (3.02)	7.29 (10.97)	3.59 (10.58)	3.62 (2.03)	7.04 (11.04)
Vancouver	2.80 (11.37)	3.27 (0.67)	5.96 (11.38)	2.80 (11.37)	3.27 (0.67)	5.96 (11.38)
Bern	0.98 (13.63)	4.18 (1.54)	5.14 (13.37)	1.31 (13.80)	3.15 (0.61)	4.42 (13.57)
Global mean	1.45 (14.89)	3.78 (1.76)	5.17 (11.62)	2.44 (11.00)	3.38 (1.41)	5.74 (10.93)

Note: The table shows arithmetic means of log returns for every city in our sample. Standard deviations are in parenthesis. Returns are split up into capital gains and rent returns, log returns are calculated for each category separately. The full sample time period is city specific and refers to the minimum coverage of price and rent data by city depicted in Table 1. The post 1950 period covers the same time period per city from 1950-2018. In the data we use right now, some years are still interpolated (esp. Germany). Returns from interpolated series are included here. This table uses alternative benchmarks for current rental yields.

1.S.2 Analysis of outliers

In this subsection of the data appendix, we analyze the primary outliers in the city-level housing return series. In an effort to validate these observations, we have gathered both quantitative and qualitative evidence for each outlier. In all cases, we have found evidence of significant price movements in the market that align with and support our series.

Bern 1950 (40.67 log return):. The first rental market dregulation started in this year and led to strong price increases (Müller, 2021)

Bern 1950 (40.67 log return):. The local newspaper "Berner Tagwacht"[292] mentions in several articles published that year the extraordinary rise of land prices as part of the housing problem. A land policy in place in force in 1964 was meant to restrict price increases and increase land supply.

Cologne 1950. : Post-war Cologne still experienced a severe housing shortage due to war destructions. Restrictions on new unregulated constructions as well as the return of previously evacuated persons and migration to urban labor markets severed the housing crisis, as a systematic review of all housing articles in the local newspaper Kölner Stadtanzeiger reveals.

Cologne 1969.

Frankfurt 1959. : The Frankfurter Allgemeine reports that the Bundesbaulandgesetz of 1960 meant an end of the price regulation for land plots for new construction. In anticipation of this law, investors went into buying land plots driving price increases, see e.g. "Chaos auf dem Frankfurter Grundstücksmarkt" reported on 28.12.1960 or "Der verlogene Preisstop fr̈ Grundstücke" on November 2nd, 1959.

Helsinki 1951 (40.43 log return):. - The Summer Olympic Games were hosted in Helsinki in 1952. In preparation for the games, the city embarked on large-scale public works construction projects. In addition to the Olympic village, stadium, and venues, a new, modern airport was constructed; tens of kilometers of roads were paved; and the first traffic lights were installed in the city (Wickström, 2002).

Madrid 1953. : The papers report a decree issued by the Ministry of Justice on the 17th of May 1952. In the first article (image below), the suspension of rent increases established in Article 118 of the Ley de Arrendamientos Urbanos 1946 is lifted. This was to be applied from the 1st of January 1953. As reported by the newspaper Pueblo: Diario del Trabajo Nacional (20/01/1953), this was to result in increases ranging from 5% to 10%. The Mundo Obrero (Número 13 – May 1953) reports an additional increase in the price of rents in March of 1953.

292. (E.g. https://www.e-newspaperarchives.ch/?a=d&d=TGW19630108-01.2.20&e=——196-de-20-TGW-1–img-txIN-bodenpreise—-1963—0—–

Madrid 1987 (52.01 log return) and Barcelona 1988 (49.3 log return):. The late 1980s saw a large real estate and construction boom in Spanish cities. As Martinez Pagés and Maza Lasierra (2003) write in a Banco de Espana Working Paper: "In real terms, average house prices in Spain between 1984 and 1991 would have increased by 106%" (12).

Madrid 2000 (45.93 log return):. After a period of price stagnation in residential housing markets during the mid-1990s, a larger Spanish housing boom famously ran its course from 1998 to 2006, again with its largest effects in big Spanish cities. As Martinez Pagés and Maza Lasierra (2003) show, housing prices in Spain rose by 25% at the national level in 2000 and they claim that prices in Madrid increased probably even more, however, they do not have the data to show that.

Milan 1989 (47.23 log return):. In the late 1980s, Italian home prices grew very strongly. Breglia (2016) documents in an I.STAT presentation in 2016 that from 1987-1992 they increased 83% nationwide (6). Furthermore, using BIS data, Ball (1993) documents that in 1989 Milan residential property prices rose 33%.

New York 1968:. New York City experiences a "great apartment squeeze", as the New York Times reports, there are strong house price increases due to a shortage of apartments, which drive the middle class out of the city in the year 1968 (and 1969).[293]

Paris 1957:. This year saw a slowdown of the construction sector, generally high inflation pressure, lower mortgage lending leads to strongly rising house prices, as reported in the daily newspaper Le Monde (09/02/1958). This was a period of genereally strong inflationary pressure which led to the introduction of a new Franc (Laux, 1959).

Sydney and Melbourne 1950 (68.34 and 88.8 log returns, respectively):. During the WWII and post-war period (1942-1949), Australia imposed strict home price controls. When the controls were lifted in 1949, this led to a rapid price appreciation across Australia. As Stapledon (2007) describes, "With the lifting of controls, house prices rose very sharply. For Sydney, the median price for detached houses rose from the median pegged price of $2400 in 1942-49, by 119% to $5250".

Tokyo 1952:. IIa (in Japan Times; December 15, 1952) writes that "the stock market is showing aspects rarely presented before", pointing to an increase in the price of real estate stocks and stating that Heiwa Real Estate is "much in speculative favor." The practice of speculative buying is, in this case, related to the practice of reassessment of business assets. Reassessment was done "by raising the values of

293. https://www.nytimes.com/2013/01/20/realestate/what-is-middle-class-in-manhattan.html, see exhibit 1.

assets up to the market prices as of February, 1949, which are taken as the standard amount, and then by deducting the prices of the worn and torn assets, the balance being taken as the limit amount" (IIa, in Japan Times; December 15, 1952). The profits that could be accrued from the reassessment of business assets was especially high in this period, due to the "relatively high price level isolated from international economy". Explaining this development, an article earlier in the year speaks of a primarily internal boom, related to the Korean war boom and in anticipation of Japan's rearmament. This led to internationally high prices, causing depression in the export trade and "simply wallowing in internal inflation". It thus is in view of these inflationary pressures that the practice of reassessment of business assets came to be particularly profitable, especially in the case of real estate stock "on account of the scarcity of the shares."

Tokyo 1973 (40.67 log return):. A large speculative boom in Tokyo land prices in the 1973-1974 period has been well-documented in different papers. As Ito and Hirono (1993) write, "Historically, the sudden, sharp increase in land prices in Tokyo occurred in 1961-62, 1973-74, and 1986-87, about once in a decade. Anyone who held the land through these periods were better off", which drove large capital gains for Tokyo real estate asset holders.

Tokyo 1986 (48.52 log return):. This year marked the beginning of the 1980s Japanese housing bubble. As Okina, Shirakawa, and Shiratsuka (2001) write in a Bank of Japan policy paper, the explosive rise in Tokyo land prices began in 1986 (chart on p. 400). Causes included aggressive risk-taking by financial institutions coupled with financial deregulation. More recently, LaPoint (2020) constructed quality-adjusted housing price series for japanese municipalities and shows that prices rose by 58% between 1986 and 1987 in Tokyo.

Vancouver 1981 (43.64 log return):. Vancouver underwent a large but short-lived property boom in the late 1970s to 1981. A Canadian news article writes, "As the city prepared for Expo 86, the average Vancouver [detached] house price more than doubled from $86,000 in January 1980 to $177,000 in January 1981." (Data from Real Estate Board of Vancouver). Sharp interest rate hikes (to 21% by the summer of 1981) did quickly reduce home prices, but prices soared during the boom years.

Appendix 1.T US data set

The within country US data set covers 316 MSAs on decadal frequency between 1950 and 2010 and additionally the year 2018. The core of this data set is the data constructed by Gyourko, Mayer, and Sinai (2013) for the decades from 1950 to 2000. It is built using data from the US *Census on Housing and Population*. The authors aggregate the data such that MSA borders are constant over time. For details please refer to the cited paper. In Figure 1.T.1 we show a map with the location of the MSAs in our sample.

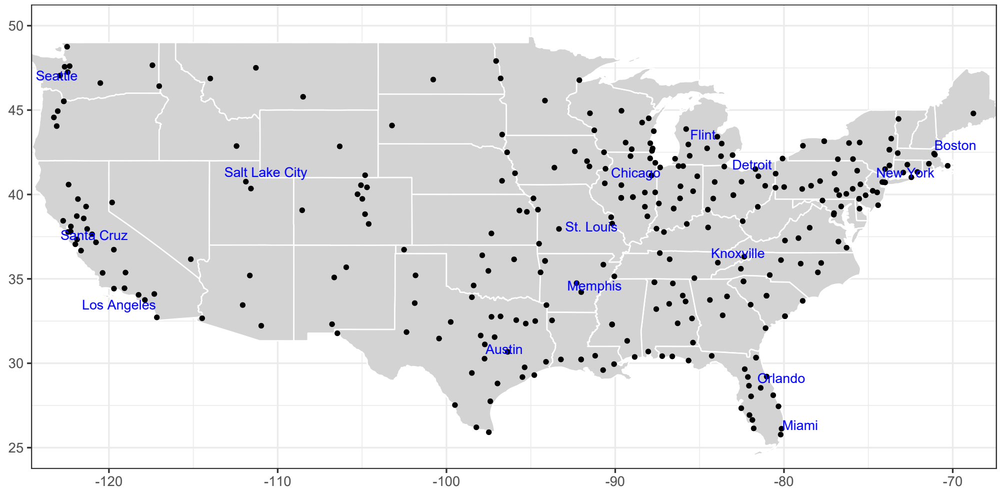

Figure 1.T.1. Geographical distribution of the American MSA sample

Note: Latitude and longitude are given on the y- and x-axis, respectively. The map was built using the shape file in Bureau (2018).

We extended this data set to also cover the years 2010 and 2018 using data from the *American Community Survey* (ACS).[294] This nationwide survey is the replacement of the long form of the former US census after 2000 and is also conducted by the U.S. Census Bureau. It includes over 3.5 million households every year and asks detailed questions on population and housing characteristics. We use information on aggregated housing value and aggregated rents from the tables B25082, B25075, B25065 and B25063. The main drawback of this source is that only a limited number of geographies is published. We use the one-year estimates, which only include data on counties with more than 65,000 inhabitants.[295]

To construct the data set for the years 2010 and 2018, we use county-level data and merge counties to MSAs following the replication files by Gyourko, Mayer, and Sinai (2013). As the ACS does not cover all counties, for 161 of the total 316 MSAs at least one county is missing or has missing price or rent data in at least one of the years 2010 and 2018. We assume that housing returns in missing counties have been equal to the average of the counties covered within each MSA. As we are still able to cover the largest counties within each MSA, the resulting bias is probably

294. Unfortunately, the 2010 and 2020 Census did not include questions on housing anymore.
295. The 1-year supplemental estimates do not publish information on aggregated rents and housing values. 5-year estimates cannot be used due to the varying time the data was surveyed, which might induce a considerable bias.

small. Most importantly, our main results are robust to restricting our sample to only the 155 MSAs with full data coverage in 2010 and 2018.

To construct housing returns, we approximate capital gains and rental yields based on aggregated housing values and rents. First, we assume constant yearly house price growth within MSAs between the (decadal) data points, such that we compute yearly capital gains from the total capital gain between the respective and the previous data point. Second, gross rental yields are constructed as the inverse of the price-rent ratios calculated by Gyourko, Mayer, and Sinai (2013) and adjusted downwards for maintenance costs and depreciation. Following Jordà et al. (2019), we assume that one third of gross rents is spent on these costs.[296] For the return comparisons, we average rental yields between the respective and the previous data point within each MSA, such that the time coverage of capital gains and rental yields is the same.[297] This way, each data point of both return components can be interpreted as decadal averages within MSAs over the preceding decade. Total housing returns are calculated as the simple sum of these capital gains and rental yields. We are not able to use rent returns because of the decadal frequency of the data. Decadal rental yields are, however, a decent approximation of yearly rent returns, because yearly capital gains are small, such that the difference between rental yields and rent returns is negligible.

Summary statistics of the final housing returns data set can be found in Table 1.T.1.

Appendix 1.U German data set

We built a data set for German cities using data from a German real estate agents organization. The final data set covers 42 medium-sized and large German cities for the period between 1974 and 2018 (long data set) and as many as 127 West German cities from 1992 until 2018 (wide data set). In Figure 1.U.1 we show a map with the geographical distribution of the cities. The black dots indicate the cities in the long-run data set, while the grey dots indicate the cities in the short-run data set. The data is taken from yearly reports of the largest real estate agents

296. This assumption potentially neglects cross-sectional differences in maintenance costs and depreciation as share of gross rents. Any resulting bias will, however, work against us for two reasons: First, for similar properties, rents will be significantly higher in the larger cities, but cross-sectional differences in maintenance costs and depreciation will be low. Second, the share of land value in total housing value will also be higher in large cities, reducing the share of maintenance costs and depreciation in housing value mechanically.

297. This procedure is the same as a linear interpolation of rental yields. The way we approximate rental yields for each data point does not influence our main results. All results look very similar if we use beginning or end of period rental yields. Pairwise correlations of rental yields between MSAs of two subsequent data years are between 0.60 and 0.86 and highly significant.

Table 1.T.1. Summary statistics of US MSA-level log housing returns

	Mean	StdDev	Min	Max
Population 1950	340075.53	748199.80	4286.00	8627356.00
Capital gain 1960	2.20	1.10	-0.22	7.06
Rental yield 1960	4.36	0.58	2.81	7.17
Total return 1960	6.47	1.28	3.17	13.62
Capital gain 1970	0.85	0.87	-1.53	3.24
Rental yield 1970	4.58	0.52	3.21	6.22
Total return 1970	5.39	0.95	2.76	8.26
Capital gain 1980	2.93	1.53	-0.75	7.62
Rental yield 1980	4.19	0.51	2.76	5.69
Total return 1980	7.00	1.41	3.22	10.48
Capital gain 1990	0.37	2.53	-7.03	8.22
Rental yield 1990	3.89	0.64	1.80	5.32
Total return 1990	4.26	2.17	-2.93	11.71
Capital gain 2000	1.65	1.73	-3.45	5.89
Rental yield 2000	3.80	0.68	1.65	5.66
Total return 2000	5.38	1.95	-0.63	9.13
Capital gain 2010	1.92	1.37	-2.92	6.19
Rental yield 2010	3.37	0.65	1.47	5.44
Total return 2010	5.23	1.28	0.72	9.25
Capital gain 2018	0.69	1.68	-3.94	7.43
Rental yield 2018	3.25	0.71	1.11	5.54
Total return 2018	3.92	1.59	-1.37	8.46
Observations	316			

Note: The table contains summary statistics for the U.S. MSA-level data set. All return variables are measured in log points. The data is constructed using the data from Gyourko, Mayer, and Sinai (2013) (1950-2000) and extended using the ACS (2010, 2018).

association in Germany.[298] These include data on apartment prices, apartment rents and price-rent ratios for a varying sample of cities. In the long data set, we include all cities that have price and rent data starting in 1974 and including 2018 and have coverage for prices and rents for a minimum of 35 years in-between. In the wide data set, we include all cities that have price and rent data starting in 1992 and including 2018 and have coverage for prices and rents for a minimum of 20 years. Price and rent data for missing years is linearly interpolated.

To construct the yearly reports, the real estate agents association collected data from members located in each specific city relying on their local expertise. Prices and rents are given as mode values within each city. Rents are given for three con-

298. The *Immobilienverband Deutschland (IVD)* and one of its predecessors, the *Ring deutscher Makler* (RDM).

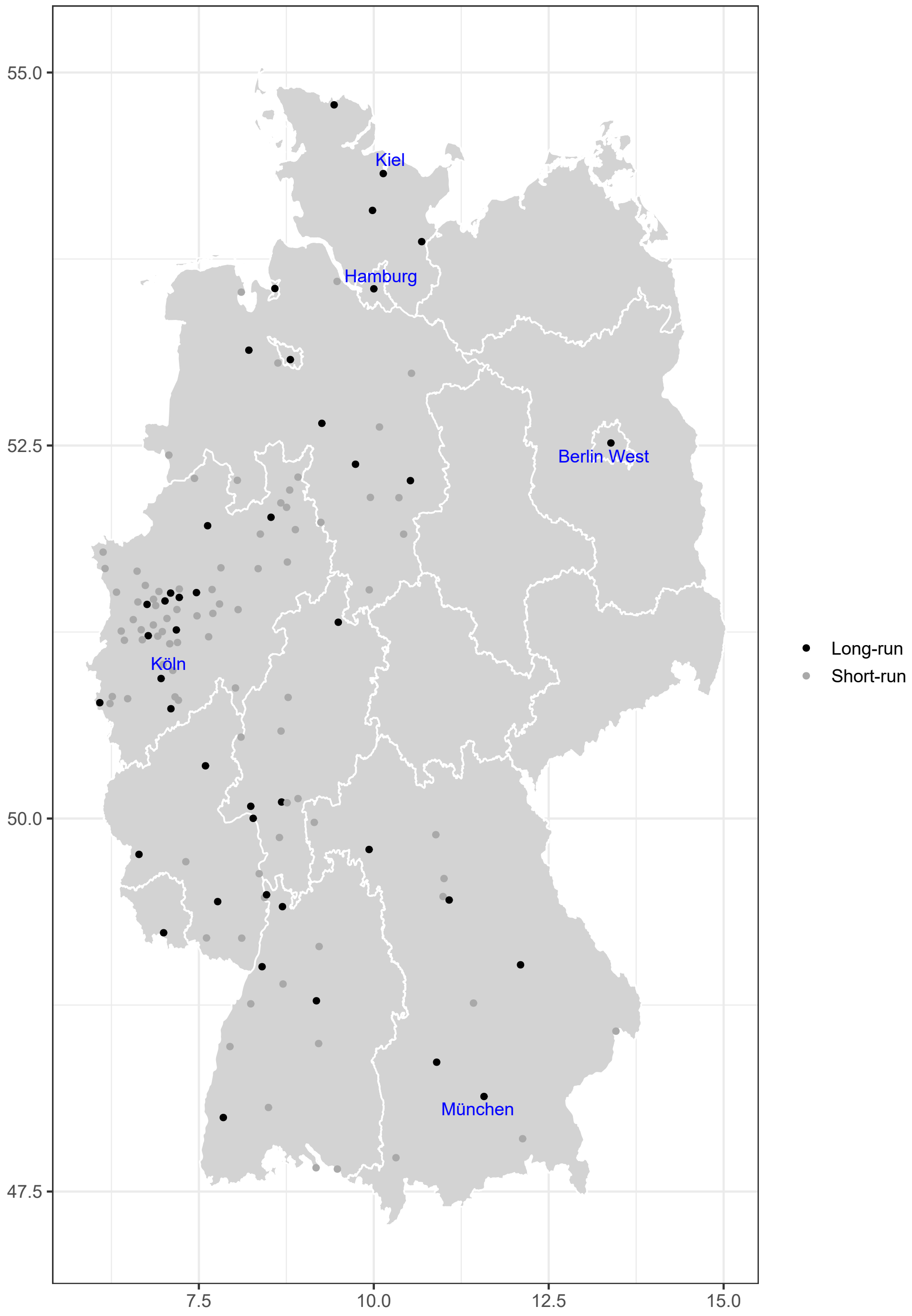

Figure 1.U.1. Geographical distribution of the German city sample

Note: Latitude and longitude are given on the y- and x-axis, respectively. The map was built using the shape file in Hub (2019).

struction categories, until 1948, after 1948 and for new construction in the respective year, and are, for each category, additionally separated in three different quality bins. Flat prices are separated into four different quality bins and from 2005 onward additionally into new and existing construction. To get a constant quality index, we exclude new construction and build a price and a rent index using a chained matched model approach and simple averages over the non-missing category and quality bins.[299]

Additionally, the data source also provides mode price-rent ratios for residential investment buildings for two construction periods, before and after 1948, from 1989 onward. We calculate gross rental yields as the inverse of these mode price-rent ratios and afterwards take a simple average over the two construction periods. The stated price-rent ratios are already net of running costs and vacancy rates. To calculate net rental yields, following Jordà et al. (2019), we assume that one third of gross rents is used for maintenance and depreciation.[300] For the years prior to 1989 and the missing years in-between,[301] we use the rent-price approach also used to extrapolate rental yields in our main data set. Out of these net rental yield estimates we calculate rent returns using the city-level apartment price indices.

We merge the price and rent indices with CPI data from the JST database until 2013 and IMF for 2014 until 2018 to calculate real price and rent series. We use these real price series to calculate yearly capital gains. We add up these with the rent return estimates to get total housing returns for each city and year. Finally, we take logs of all our return series. We also merge our data to population data for German municipalities (*Gemeinden*) from the statistical office of Germany.[302] We take end of year population for 1975 and 1989, such that we are able to use population at the beginning of our sample period, respectively, and, therefore, our analysis does not suffer from any selection or survivorship bias. In Germany, municipalities cover the complete city, but exclude the hinterlands.[303] Therefore, municipalities are the preferred administrative unit to compare city size. Moreover, the data from the IVD also used municipalities as administrative regions for their city samples.

Summary statistics for both German data sets can be found in Table 1.U.1. Additionally, Figure 1.U.2 plots city-level gross rental yields across the German city distribution, as calculated by local real estate agents in 2018. Although gross rental

299. We use a simple average, as data on the distribution of the different bins within the housing stock is not available. Using simple averages has the advantage that the weighting of the various bins is the same for every city, such that differences between cities cannot be due to differences within the quality of the housing stock.
300. As already stated above, this assumption neglects cross-sectional differences in these costs, but any resulting bias will work against us.
301. Price-rent ratios are missing for approximately 9.4% of city-year pairs from 1989 onward.
302. Data is taken from the *Gemeindeverzeichnis* from the *Statistisches Bundesamt*.
303. In contrast to counties.

yields vary considerably within size bins, a clear negative relation between city size and gross rental yields is visible in the raw data.[304]

Table 1.U.1. Summary statistics of German city-level log housing returns

	Long data set				Wide data set			
	Mean	StdDev	Min	Max	Mean	StdDev	Min	Max
Population 1975	417029.48	413298.12	30978.00	1984837.00	197296.69	286531.28	21896.00	1984837.00
Population 1998	400584.93	410918.74	30290.00	2130525.00	191571.90	281125.67	21221.00	2130525.00
Capital gain	-0.20	8.69	-59.92	42.70	-0.56	6.61	-42.93	39.21
Rent return	4.79	1.21	1.61	12.91	5.55	1.12	2.04	12.91
Total return	4.60	8.61	-53.77	47.34	5.03	6.44	-37.04	44.34
Observations	1848				3302			

Note: The table contains summary statistics for both German city-level data sets. The long data set covers housing returns between 1975 and 2018 for 42 cities and the wide data set between 1993 and 2018 for 127 cities. All return variables are measured in log points.

304. Hilber and Mense (2021) show that, although the gap in rental yields between London and the rest of England changes over the cycle, rental yields are always smaller in London, even at the trough of the cycle.

1.U.1 Additional results

Table 1.U.2. Distribution of housing returns (log points) by size of city, US 1950-2018

	1a	1b	2	3	4	5	6	7	8	9	10a	10b
Total return	5.75	5.65	5.46	5.44	5.55	5.47	5.41	5.26	5.37	5.25	5.19	4.93
Rental yield	3.96	3.94	3.93	3.93	4.19	4.13	3.96	3.98	3.99	3.83	3.48	3.32
Capital gain	1.87	1.78	1.59	1.57	1.42	1.39	1.5	1.33	1.43	1.47	1.77	1.66
N	16	16	32	31	32	31	32	32	31	32	16	15

Note: All returns are log returns. Cities are divided into bins based on the size of MSA population in 1950. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins (1a, 1b, 10a, and 10b) split the smallest and largest deciles in half. As the data for American MSAs only exist in decadal steps, we are not able to construct rent returns. Rental yields are, however, a decent approximation of rent returns.

Table 1.U.3. Distribution of housing returns by size of city, Germany 1993-2018

	1a	1b	2	3	4	5	6	7	8	9	10a	10b
Total return	6.01	5.00	4.89	4.80	4.84	5.15	4.66	4.82	5.39	5.04	5.39	4.88
Rent return	6.57	5.99	5.56	5.86	5.82	5.55	5.34	5.47	5.59	5.13	5.08	4.62
Capital gain	-0.61	-1.06	-0.72	-1.11	-1.04	-0.42	-0.72	-0.69	-0.22	-0.11	0.32	0.25
N	7	6	13	13	12	13	13	12	13	13	6	6

Note: All returns are log returns. Cities are divided into bins based on the size of city population in 1989. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins (1a, 1b, 10a, and 10b) split the smallest and largest deciles in half.

Appendix 1.V Corelogic deed data set

This section describes in detail the steps that were taken to treat the raw transaction data from the Corelogic deed data set. Our main goal was to remove all data entries corresponding to non-normal sales, i.e. sales which do not correspond to normal market real estate transactions. In the rest of this section we make the concept of market sales clearer, by explaining the steps we took to remove all transactions that did not correspond to this definition. When organizing the data set we took the following steps:

(1) We first exclude all transactions where there was evidence that the contractual parties did not act independently of each other, i.e. where the buyer or the seller was significantly influenced in the process. Typically, these kinds of transactions take place between family members or companies with the same shareholders. Using the *Primary Category Code* from Corelogic we exclude all transaction that are considered to be non-arm's length.

(2) We then exclude all transactions, for which the following is true:

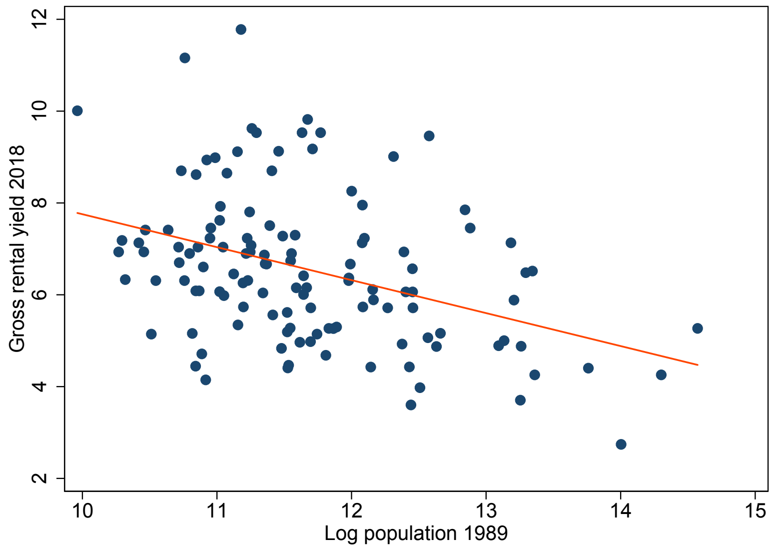

Figure 1.U.2. Correlation of gross rental yields (log points) in 2018 and log population size

Note: The figure shows city-level log gross rental yields from IVD by population in 1989 for 127 West German cities. Population data is taken from the "*Gemeindeverzeichnis*" of the German Statistical Office.

- The date of the transaction is missing.
- The transaction amount was wrongly typed, i.e. it contains letters, or it is missing.
- The transaction amount is smaller than $2000 at the time of purchase
- The transaction took place before 1990.
- The zip code or county FIPS code or the house number field is missing.
- The number of buildings involved in the transaction is larger than one.
- The transaction is considered a partial sale or a lease by Corelogic.
- The transaction is based on a quit claim deed.
- The transaction of a house which has been substantially renovated after 1996.
- The transaction is identified as being part of a multiple sale, i.e. a sale in which different properties are assigned to the same deed.

(3) In a next step, we identify and eliminate duplicates. We first identify complete duplicates, i.e. observations for which all fields are identical, and almost complete duplicates, i.e. observations which have the same internal id, sale date, zip code, house number and transaction amount. Whenever we identify duplicates we leave only one observation per group of duplicates.

(4) We then identify the repeat-sales using Corelogics' unique property identifier alongside the FIPS code, the zip code and the house number.

(5) To make sure we have sufficient observations per MSA, we then drop all MSAs, which have less than 3000 repeat sales in the period between 1990 and 2020.

(6) We also exclude all repeat-sales with holding period shorter than one year, as well as, all sales, which are considered by *Corelogic* to be associated with new construction.

(7) In a final step, we exclude all MSAs, for which the first recorded sale in the data set takes place after 1992. This way we ensure that more recent MSAs are not included in the final data set.

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Chapter 2

Price Uncertainty and Returns to Housing*

2.1 Introduction

Buying a house is the most important financial decision that households make in their lifetime. Understanding the factors driving the willingness to pay for a house is, therefore, of great importance. While several papers have examined the role of location, credit conditions, income and other factors (e.g. Mian and Sufi, 2009; Van Nieuwerburgh and Weill, 2010; Duranton and Puga, 2015), in this paper, I focus on how uncertainty about the market value of a house affects its transaction price and return.

This uncertainty, defined as the expected variance of the distribution from which the price of a house might be drawn at a point in time, differs substantially across individual houses (Kotova and Zhang, 2021; Jiang and Zhang, 2022). There are different factors that can contribute to price uncertainty in housing markets. The heterogeneity and illiquidity of houses introduce uncertainty about the outcome of the bargaining process between buyers and sellers (Goetzmann, Spaenjers, and

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Van Nieuwerburgh, 2021; Sagi, 2021). Additionally, houses are generally held for extended periods of time, rendering them susceptible to various shocks that can impact their fundamental value (Sinai and Souleles, 2005; Han, 2013), making them harder to value ex-ante.

However, we still know little about the extent to which price uncertainty influences the trading decisions of buyers and sellers and, consequently, impacts housing prices and returns. This is a challenging task, as it requires highly granular data on housing markets. Using a newly-collected transaction-level dataset covering the universe of apartment transactions over the last 40 years in four of the largest German cities[1], I am able to shed light on this issue. I find evidence that this uncertainty is priced in housing markets: apartments with higher price uncertainty trade, on average, at lower prices. The magnitude of the effect is large, I estimate that apartments with high price uncertainty trade at a price that is, on average, 5% lower than comparable apartments with lower price uncertainty, a result in the same order of magnitude as existing estimates of foreclosure discounts (Conklin et al., 2023).

Nevertheless, I find that these apartments can still be rented out at standard rates, resulting in higher rental yields, as measured by the ratio of net rental income to transaction price. I then measure total returns as the sum of rental yields and capital gains at the apartment level. I find that apartments with greater price uncertainty tend to yield higher total returns, due to higher rental yields. Again, these differences are economically significant. The data suggests an average annual return premium of 50 basis points for apartments exhibiting greater price uncertainty. This is approximately 10% of the average yearly total housing return in Germany over the past four decades.[2]

I rationalize these findings through the lens of a bargaining model. The model features a risk-averse housing investor who acquires a property for renting and future sale. Consistent with my empirical results, the model predicts that properties with greater re-sale value uncertainty will transact at lower prices and have higher rental yields. Assuming that matching frictions drive the price uncertainty, the model also predicts that total returns are higher due to increased rental yields. Confirming the assumptions of the model, I find that apartments with greater price uncertainty are traded in smaller and less liquid markets, which suggests that matching frictions in the housing market underlie the uncertainty surrounding transaction prices.

The primary data source I use in this paper is a transaction-level dataset introduced in Amaral et al. (2023), which contains detailed information on the universe of residential real estate transactions in large German cities over the last half-century. The dataset provides comprehensive information on property characteristics as well as transaction types. This feature enables me to control for differences in

1. Berlin, Hamburg, Cologne and Duesseldorf.
2. I take the estimates for Germany from Amaral et al. (2021).

observable property characteristics and effectively identify transactions of the same properties over time. The data set also includes information on the realised rental income after costs, which allows me to build net rental yields at the property level.

My focus is on the most prevalent housing type in large German cities: apartments. The market for apartments in large German cities provides an ideal setting to examine the relationship between price uncertainty and housing returns. In contrast to U.S. cities (Glaeser and Gyourko, 2007), there is minimal segmentation between the homeownership and rental markets for apartments in large German cities. Owner-occupied and rental apartments exhibit only marginal differences in terms of their location and characteristics.

Following Jiang and Zhang (2022), I measure price uncertainty at the apartment transaction level as the predicted variance of the pricing error from a hedonic housing price model. I provide evidence that the error in the hedonic model is not driven by omitted variable bias or is simply noise. I do this by showing that the errors are spatially independent and that their magnitude is highly persistent over time within apartments.

Then, I introduce the measure of price uncertainty into a hedonic model of house prices and show that higher uncertainty significantly predicts lower transaction prices for all cities in my sample. Importantly, I also show that properties with higher price uncertainty do not have lower demand, as proxied by online search behaviour, thus reinforcing that uncertainty is being priced in. These effects are economically very relevant: transitioning from the lowest to the highest quintile of price uncertainty predicts a decrease in the final transaction price by approximately 5% to 7% for properties transacted in the same neighborhood and year-quarter, while controlling for property characteristics.

However, the effect is notably weaker for rents. Rental rates are similar across properties with different price uncertainty. The rationale behind this outcome is that such apartments face greater illiquidity in the sales market compared to the rental market. This aligns with the fact that in large German cities, the rental market is larger and more liquid than the sales market. I then find that properties with higher price uncertainty exhibit, on average, higher rental yields. Transitioning from the lowest to the highest quintile of the price uncertainty distribution predicts an increase of between 35 and 60 basis points in rental yields for transactions during the same year-quarter in the same neighborhood, while controlling for property characteristics.

By identifying repeated sales of the same apartments over time, I am able to construct property-level capital gains, which, when combined with rental yields, provide measures of property-specific total returns. I then find that apartments with higher price uncertainty experience, on average, the same rate of price appreciation as other apartments. In other words, the data shows that price uncertainty is uncorrelated with the level of capital gains in housing markets. Finally, I show that properties with higher price uncertainty have, on average, higher total returns, driven by rental yields.

To make sure my results are not driven by time-varying market conditions, I employ portfolio sorting methods and hedonic regressions to construct a time series of prices and returns for properties with high and low price uncertainty. I show that portfolios with high price uncertainty yield higher total returns, and this return premium is not driven by heterogeneous exposure to systemic risk as measured by the returns on city market portfolio. Additionally, I conduct a battery of robustness tests to ensure that my results are not influenced by measurement error and to exclude alternative mechanisms. Importantly, I do not find that properties with higher price uncertainty have lower demand based on online search behaviour.

I map these empirical findings to a bargaining model featuring a risk-averse investor, who faces uncertainty regarding the future rental income and resale value of the house. Intuitively, the investor's risk aversion explains why properties with greater price uncertainty exhibit lower transaction prices and higher rental yields. More interestingly, the model reveals that the impact of price uncertainty on capital gains depends on the source of that uncertainty. Under the assumption that price uncertainty arises from matching frictions, the model predicts that increased price uncertainty does not result in higher capital gains, as supported by the data.

In line with the mechanism of my model, I find that apartments with higher price uncertainty are traded in smaller markets. More specifically, there is a lower number of similar properties on the market, making it more challenging to price these apartments.[3] Additionally, I show that properties with higher levels of price uncertainty are less liquid. On average, they have a longer expected time on the market and a lower probability of sale. Furthermore, the final transaction price is, on average, significantly lower when compared to the original asking price.

Related literature. This paper contributes to the literature on price dispersion in housing markets (Piazzesi and Schneider, 2016; Giacoletti, 2021; Sagi, 2021) by showing how the interaction between rental and sales markets affects transaction prices and returns. Jiang and Zhang (2022) show that price uncertainty impacts the quality of housing as collateral and, consequently, negatively affects the credit conditions offered by banks. I complement this work by showing that price uncertainty also influences transaction prices and returns.

This paper also speaks to the literature on the risk factors driving returns to housing (e.g., Cannon, Miller, and Pandher, 2006; Han, 2013; Amaral et al., 2021; Demers and Eisfeldt, 2022). While this literature has primarily focused on identifying systemic housing risk factors, this paper provides evidence that property-specific idiosyncratic risk factors are priced in housing markets.

3. This concept builds on the idea of house atypicality (Haurin, 1988).

My research also connects to the literature on decentralized asset markets. Duffie, Gârleanu, and Pedersen (2007) develop a search-and-bargaining model for financial assets traded in decentralized markets to understand how trading frictions affect asset prices. Gavazza (2011) constructs a model of the commercial aircraft market to illustrate how market thickness affects liquidity and prices. The author shows that airplanes traded in thinner markets typically trade at lower prices, mirroring the effect I find for housing assets. The interplay between liquidity in the rental and sales market aligns with the theoretical framework presented in Pagano (1989), who examines how trading frictions can influence the relationship between market size and asset liquidity across various markets and thus determine the distribution of trading activity.

The rest of the paper is structured as follows. Firstly, I present the data and provide evidence on market liquidity in the German housing market. Secondly, I describe the measurement of price uncertainty and present the empirical framework. Thirdly, I show that properties with higher price uncertainty are sold at a discount and have higher returns. I present the data and provide evidence on market liquidity in the German housing market. Fourthly, I derive a theoretical framework and characterize the optimal bid of a risk-averse investor when facing uncertainty about future cash-flows. Fifthly, I provide empirical evidence linking price uncertainty to market size and liquidity at the property level. The last section concludes.

2.2 Data

In the empirical analysis of this paper, I combine three distinct datasets. The first dataset comprises comprehensive transaction-level information on the universe of real estate transactions in major German cities dating back to the 1980s. I employ this dataset to estimate price uncertainty and construct two market liquidity measures for four large German cities. The second dataset, which I developed from scratch, contains net rental values in German cities based on property size, age, and location, spanning from the 1980s onwards. I use this data set to provide rental income information for those observations for which it is missing in the main transaction data set. The third dataset encompasses real estate advertisements in Germany since 2010. I merge this dataset with the transaction-level data to obtain additional liquidity measures at the transaction level. I will now provide a more detailed description of each dataset.

Transaction-level data set. - This data set, introduced in Amaral et al. (2023), consists of transaction-level data encompassing all residential real estate transactions in 20 major German cities dating back to the 1960s. The underlying data is sourced from the local real estate expert committees, known as "Gutachterausschüsse," who receive comprehensive information about each real estate transaction from notaries. This valuable information encompasses the transaction price, date, as well as various property characteristics such as size, location, and building year. Additionally, it includes details about the type of transaction, including whether it was conducted at arm's length or not. In many instances, this data is further enriched by gathering additional information directly from buyers and sellers regarding the property, such as whether the property has a garage or not. The scope of this novel data set is, to the best of my knowledge unique, in that existing transaction-level data sets only contain representative sales information for a shorter period of time.[4]

For the main empirical analysis, I only use data on sales of apartments. The reason for this is twofold. Firstly, the housing stock in large German cities is mostly composed of apartments and therefore there are considerably more apartment sales than of other types of housing. This contrasts with most cities in the U.S., where the predominant type of housing is single-family. Secondly, apartments are more homogeneous types of housing than single-family or multi-family housing. This increases the statistic precision of the hedonic analysis, which I will carry on later.

Before conducting the empirical analysis, I ensure the integrity of the transaction data by meticulously filtering out non-arm's length sales. This encompasses a range of transactions, such as property sales between relatives, leaseholds ("Erbbau"), package sales involving multiple properties sold together, sales of social housing, transactions involving official government institutions at the local or federal level, foreclosures and any sales flagged by the "Gutachterausschüsse" as not aligning with genuine market prices. Additionally, I exclude all transactions that have missing information regarding the date, sales price, size, location, or building year. To enhance the sample quality, I implement supplementary cleaning procedures. Specifically, I eliminate "house flips" and cases where the reported sale price appears anomalous, as well as duplicates. This is accomplished by removing all transactions of a property if it undergoes two sales within a year or if its annualized appreciation or depreciation exceeds 40% for any given pair of sales. This approach adheres to the standard methodology established in the literature (e.g. Giacoletti, 2021). Please note that in all specifications, the sales price measure I utilize is net of additional costs that do not directly pertain to the value of the structure and land of the respective property. In other words, the sales price is adjusted for inventory costs (e.g., if the kitchen is included in the apartment sale) or additional infrastructure expenses (e.g., when the owner of the apartment is entitled to use a parking spot or garage). The valuation of these additional costs is specified in the contract and is also reported by the "Gutachterausschüsse". Table 2.C.1 presents the summary statistics of the data by city after the cleaning procedures.

Rental values data set. - To complement the rental income information provided by the "Gutachterausschüsse", I collected net rental value data from an independent

4. For example, in the case of the U.S. existing data sets, such as Corelogic, only have a reoresentative sample since the 2000s.

source. I then merge it with the transaction-level data. The rent data is obtained from the so-called "Mietspiegel", which provides rent per square meter estimates for apartments in German cities based on factors such as size, age, and location of the apartments. The rent estimates are net of utilities and maintenance costs. These rent estimates are then matched with the transaction data, conditional on the size, age, and location of the property. The specific details regarding the data source and the matching process are provided in Appendix 2.K. In the empirical section, I will present the results for both the full sample, where transactions were matched with rents based on characteristics, and for the subsample in which both transaction prices and rental income are observed for the same property at the same point in time.

Real estate advertisement data. - To be able to measure asset liquidity at the transaction property level, I combined transaction-level data with advertisement data. The advertisement data was sourced from Value AG, a German real estate company that has consistently been collecting online real estate advertisements and integrating them with data from local real estate agents, resulting in a comprehensive and extensive data set that covers the period from 2012. This data set from Value AG encompasses crucial information on property characteristics obtained from the advertisements. Leveraging this information, I employed a nearest neighbor algorithm to match the transaction data with the advertisement data.

2.2.1 Liquidity in German Housing Markets

Several studies examining the structure of decentralized asset markets have provided evidence that larger markets enhance the efficiency of matching between buyers and sellers. This effect results in reduced price dispersion and decreased uncertainty surrounding the value of traded assets (Gavazza, 2011; Sagi, 2021). In this section, I present various pieces of evidence regarding the size and liquidity of the rental and sales markets for apartments in major German cities. Overall, the empirical evidence indicates that the apartment rental market is significantly larger, thicker, and more liquid than the apartment sales market.

Using data from the largest real estate online platform in Germany for the period between 2010 and 2018.[5] For this analysis, I exclude from the original dataset all ads with missing information about price, rent, or size. Additionally, I also remove ads flagged as potential duplicates. This issue may arise when an ad is deliberately removed and then re-uploaded shortly afterward to increase its visibility.

In Table 2.1, I present various indicators for the rental and sales markets of apartments in the four cities in the sample. The second column shows the homeown-

5. The data is originally from www.immoscout.de and was provided by RWI and Immobilienscout24 (2021). The data is available from 2007 onwards, but due to issues in the identification of duplicate ads, it only becomes representative from 2010.

ership rate in 2010 by city.[6] On average, only one-fifth of the population actually resides in owner-occupied housing, while the rest rents. Similar to other developed countries, homeownership rates in German cities are substantially below the national average, which has remained around 45% over the last decade (Kohl, 2017).

The third and fourth columns display the average number of sales and rental ads for apartments per year by city.[7] On average, each year there are four times more rental ads than sales ads, confirming that the rental market is not only larger in terms of its inventory but also in terms of the number of properties available.

However, what truly matters is the number of potential buyers per ad, i.e., the market thickness. To approximate the market thickness, I use data on the number of times the seller was contacted by potential buyers through the website for a specific ad. For clarification, this metric is not equivalent to hits per ad. To contact the seller, a potential buyer (or renter) must click on the ad and then select the 'Contact Seller' option. The average number of contacts for sales and rental ads is displayed in columns 5 and 6. On average, rental ads attract four times as many customers showing explicit interest compared to sales ads, indicating that the rental market is considerably thicker.

Finally, in columns 7 and 8, I present the average number of days that sales and rental ads remain on the website. Not surprisingly, we observe that sales ads stay, on average, twice as long on the website, suggesting that the time on the market is substantially shorter for apartment rentals than for apartment sales.[8] Overall, there is considerable evidence that the rental market for apartments is larger and more liquid than the sales market in large German cities.

Table 2.1. Summary statistics for apartment sales and rentals by city, 2010-2018

		# ads per year		Contact clicks per ad		Duration of ads (in days)	
City	Homeownership rate (in %)	Sales	Rentals	Sales	Rentals	Sales	Rentals
Berlin	13.7	25767	109804	4	32	26	18
Cologne	26.7	7086	27517	12	50	40	20
Duesseldorf	21.6	6567	28544	10	28	35	21
Hamburg	21.4	9883	27657	8	33	36	17

Note: The homeowneship rate refers to 2010 and the data source is Eurostat. The rest of the data refers to the period 2010-2018 and is based on own calculations with data from *www.immoscout.de*, which provided to me by RWI and Immobilienscout24 (2021). "Duration of ads" measures the days between the day the ad was posted and the day the ad was removed. "Contact clicks per ad" refers to the average amount of times that the seller was contacted by potential buyers via the website about the ad.

6. The data is obtained from Eurostat.
7. I determine the year based on the initial date of the advertisement.
8. Furthermore, rental ads potentially have a much higher chance of actually resulting in a rental contract than sales ads have of resulting in a sales contract.

2.3 Measurement and Empirical Framework

Following the real estate literature (e.g Kotova and Zhang, 2021), I measure idiosyncratic price deviations at the apartment transaction level as the difference between the transaction price and the expected market value, which is determined using a hedonic regression estimated on apartment repeat sales.[9]

For each city separately, I regress the natural logarithm of the transaction price for property i in year-quarter tq on a time-invariant apartment fixed effect, y_i, year-month fixed effects, η_{tm}, year-quarter-neighborhood fixed effects, $\kappa_{n,tq}$, and a second-order polynomial function of apartment characteristics (age and size) interacted with year fixed effects, $f_c(x_i, ty)$:

$$ln(p_{i,tq}) = y_i + \eta_{tm} + \kappa_{n,tq} + f_c(x_i, ty) + u_{i,tq}, \tag{2.1}$$

where $u_{i,tq}$ is a mean-zero error term with variance σ^2. Specification (2.1) combines elements of repeat-sales and hedonic models of housing prices. The apartment fixed effect term, y_i, absorbs all features of an apartment, observed and unobserved, which are time-invariant, such as a balcony facing the sea or the floor number. The η_{tm} and $\kappa_{n,tq}$ terms absorb parallel shifts in housing prices in a city and in neighborhoods over time, for example due to gentrification.[10] The $f_c(x_i, ty)$ term allows apartments with different observable characteristics x_i to appreciate at different rates: for example, the $f_c(x_i, ty)$ term allows larger apartments to appreciate faster than smaller apartments, or newer apartments to appreciate faster than older apartments. I use an additive functional form for $f_c(x_i, ty)$:[11]

$$f_c(x_i, ty) = g_c^{sqmt}(sqmt, ty) + g_c^{yrbuilt}(yrbuilt, ty) \tag{2.2}$$

The functions $g_c^{yrbuilt}$ and g_c^{sqmt} are interacted second-order polynomials in their constituent components. The squared terms of the polynomial function accommodate the possibility that the effect of size and age on transaction prices may vary along the distribution. For instance, larger apartments might appreciate at a different rate than smaller apartments, and this effect may not follow a monotonic pattern. Please note that for Hamburg, information identifying the exact apartments was not available. As such, I use building fixed effects instead of apartment fixed effects to measure price deviations for Hamburg. For more details please refer to Appendix 2.C.3.

9. A very similar approach to estimate the market value is employed in Buchak et al. (2020) and Kotova and Zhang (2021).

10. More precisely, I use the definition of "Stadtbezirke" to divide the cities in different neighborhoods.

11. In principle, it would be better to estimate a fully interacted polynomial in all house characteristics. However, as argued by Kotova and Zhang (2021), that is not computationally feasible.

The residuals, $u_{i,tq}$ from equation (2.1) quantify the discrepancy between the transaction price and the expected market value of the apartments. Consequently, the squared residuals serve as a measure of price dispersion at the apartment transaction level. Table 2.2 displays the summary statistics for the apartment repeat sales for all cities in the sample.[12] In terms of the standard deviation of the residuals, Cologne has by far the lowest level, 10.1%, followed by Duesseldorf with 14.9%, Hamburg with 17.7% and Berlin with 18.2%.[13] Using the same method Kotova and Zhang (2021) estimate the standard deviation of residuals for single-family houses in California to be in the range between 11.1% and 13.5% depending on the city.

Table 2.2. Summary statistics for apartment repeat sales by city

	Berlin					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	67195	186	162.3	83.9	135	229
Size (m^2)	67195	74	28.8	53.5	67.3	89.2
Construction year	67195	1932	38.3	1903	1912	1961
Residuals, $u_{i,tq}$ (%)	67195	0	18.3	-10.9	0	11.3
Rental yield (%)	67195	3.5	1.7	2.3	3.2	4.3
	Hamburg					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	49506	306	263.6	130	234	394
Size (m^2)	49506	76	30.8	54	70	91
Construction year	49506	1974	41	1953	1978	2012
Residuals, $u_{i,tq}$ (%)	49506	0	17.8	-8.4	0	9.5
Rental yield (%)	49506	4.2	2	2.9	3.8	5
	Cologne					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	49963	140	103.6	75	112.5	170
Size (m^2)	49963	69	24.7	52.4	67	84
Construction year	49963	1968	23	1959	1971	1983
Residuals, $u_{i,tq}$ (%)	49963	0	13.6	-7.8	0	7.9
Rental yield (%)	49963	5.7	2.4	4.1	5.4	6.8
	Duesseldorf					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	25238	156	136.2	76.7	117.4	185
Size (m^2)	25238	74	28.7	54	70	90
Construction year	25238	1961	24.7	1953	1962	1976
Residuals, $u_{i,tq}$ (%)	25238	0	14.8	-8.4	0	8.7
Rental yield (%)	25238	5	2.2	3.7	4.6	5.8

Note: Table reports summary statistics for all apartment resales for Berlin (1986-2022), Hamburg (2002-2022), Cologne (1989-2022) and Duesseldorf (1984-2022). Note that before 1992 the data for Berlin refers only to West-Berlin. Prices are in nominal terms. Please note that in the case of Hamburg, the total number of sales does not refer to repeat-sales, as data on the number of the apartments is missing in the original data. Please refer to Appendix 2.C.3 for more information.

12. Table 2.C.1 in the Appendix presents the summary statistics for all apartment sales, i.e. not just the repeat sales.

13. Figure 2.C.1 in the Appendix plots the distribution of residuals, u_{it}, with the mean and standard deviation for the cities in my sample separately.

2.3.1 Stylised facts about price dispersion

While the concept of price dispersion is clear in theory, the infrequent transactions of properties, coupled with the significant heterogeneity among houses, complicates the empirical task of estimating price dispersion. Therefore, in this section, I first present additional evidence regarding the distribution of estimated price dispersion across space and over time to validate the estimates. Secondly, I will discuss several potential biases that could arise in equation (2.1) and demonstrate that the main results of the paper are not influenced by these biases. For the sake of brevity, the results in this section will be referenced in the text but will be presented in Tables and Figures in appendices 2.D and 2.J.

Distribution of dispersion across space and over time. By definition, the market value of a property should reflect the value of common property characteristics in the market. In other words, the residuals in Equation (2.1) should capture the cross-sectional variation in the idiosyncratic component of housing prices. This aligns with the bargaining model in Section 2, where, in the first period, the investor encounters uncertainty surrounding the idiosyncratic component of prices in the final period. To test whether the residuals are idiosyncratic, I now examine their spatial distribution. If Specification (2.1) is correctly defined, then we should expect the residuals to be spatially independent. To test for this, I estimate spatial correlation in the residuals, $u_{i,tq}$ using Moran's I. A positive Moran's I indicates that apartments with positive residuals are surrounded by other apartments with positive residuals. In Figure 2.D.1, I plot Moran's I for the residuals and the transaction prices. In contrast to the transaction prices, the results suggest that the residuals are spatially independent, as I cannot reject the null hypothesis of no spatial autocorrelation. In Appendix 2.D, I provide a more detailed explanation of how Moran's I is estimated and present the results of this analysis.

In the bargaining model in Section 2, I assume that the investor knows the variance of the sales price in the final period. In other words, the investor is aware of the price dispersion of a given house. To justify this assumption, it is necessary for the estimated price dispersion, $u_{i,tq}^2$, to be predictable over time. Specifically, I test for all pairs of transactions in the data set whether the variance of the residuals at the point of sale predicts the variance of the residuals at the point of re-sale:

$$u_{i2}^2 = \beta_1 u_{i1}^2 + \beta_2 hp_i + \kappa_{nt} + \lambda_m + \epsilon_{it}, \tag{2.3}$$

where u_{i2} and u_{i1} are the idiosyncratic price residuals at the points of re-sale and sale respectively of property i. hp_i measures the holding period in months for property i, while δ_m are monthly fixed effects and κ_t are neighborhood fixed effects. The results can be found in Table 2.D.1, which shows that properties sold and re-sold in the same neighborhood and in the same month show considerable persistence in their idiosyncratic price dispersion. An increase in one standard deviation of the sales' price dispersion predicts an increase in 0.66 standard deviations in the resale price dispersion. One concern is that these results are being driven by the buyers, if a specific buyer is bad at pricing a house at the moment of sale, then probably as well at the moment of re-sale. This could potentially explain the high level of persistence in the variance. To address this concern, I show that the persistence in variance is also strongly positive and statistically significant when testing the relation between first and third sale. The results can be found in Table 2.D.2 in Appendix 2.D. Additionally, the cross-sectional correlation at the point of sale and re-sale of idiosyncratic shocks is 0.66, which is higher that than most risk factors used in the stock pricing literature (Bali, Engle, and Murray, 2016). The results can also be found in Appendix 2.D.

Biases. The baseline regression model in (2.1) may yield biased results due to several factors. Therefore, I highlight potential issues that may arise and explain how I address them in the robustness analysis presented in Section 2.J of the appendix.

Firstly, in regression (2.1), I incorporate apartment fixed effects. However, this approach may pose challenges since most properties are sold only a few times within the sample period. This could potentially lead to an "incidental parameters problem" (IPP) problem, whereby the estimate $\hat{\sigma}^2$ would be inconsistent. Moreover, it is crucial to consider whether properties sold more than once are representative of the entire population of transacted properties. If these repeat sales do not accurately reflect the broader sample, the generalizability of my results could be compromised. To address these concerns, I run regression (2.1) while excluding the apartment fixed effects. The findings of this analysis are presented in Section 2.J of the Appendix, where I show that the main results remain consistent and robust.

Secondly, in my baseline regression analysis, I do not explicitly account for the influence of varying holding periods on the sales prices. It has been demonstrated by Giacoletti (2021) that longer holding periods are correlated with greater idiosyncratic shocks. To ensure that this factor is not driving my results, I conduct an additional regression analysis that incorporates holding period fixed effects. The findings of this analysis demonstrate that the results remain robust and unaffected by the inclusion of holding period fixed effects.

Thirdly, it is important to consider that sales prices may be influenced in a systematic manner by the characteristics of both buyers and sellers. If certain types of households, such as affluent ones, tend to concentrate in specific areas, then regression (2.1) already accounts for this by incorporating location fixed effects. However, it is also possible that businesses or large investment funds have the ability to negotiate more favorable prices compared to individual households. To address this potential influence, I perform an additional regression analysis that includes buyer and seller fixed effects, along with their interaction term. These controls account for whether the buyers or sellers are private companies or households. The robustness analysis presented in Section 2.J demonstrates that the results remain unaffected even after incorporating these additional controls.

2.3.2 Empirical Framework and Identification

The theoretical framework outlined in Section 2 guides the empirical tests concerning the effects of price dispersion on transaction prices and returns. While in the model, the investor adjusts the optimal bid based on the expectation of price dispersion, the price dispersion measured in the previous section reflects realized price dispersion. In other words, the residuals, $u_{i,tq}$, from Equation (2.1) are only observed ex-post and thus represent a biased measure of investors' expectations. Therefore, I approximate the information set available to a potential investor about a specific property before purchasing it. To achieve this, I employ the method introduced in Jiang and Zhang (2022). Using the observable characteristics of the properties and the transaction values of similar properties that were sold in the same period, I obtain a prediction of idiosyncratic price dispersion at the property level. More specifically, I estimate the following regression:

$$u_{i,tq}^2 = g_c(x_i, tq) + \epsilon_{it} \tag{2.4}$$

$$\hat{\sigma}_{i,tq}^2 = \hat{g}_c(x_i, tq), \tag{2.5}$$

where u^2 are the squared residuals estimated from equation 2.1 and $g_c(x_i, tq)$ is a smooth function of observable property characteristics interacted with quarter fixed effects. The characteristics are size, age and location and g is an additive function that takes the form:

$$g_c(x_i, tq) = g_c^{loc}(tq, \kappa) + g_c^{sqmt}(tq, sqmt) + g_c^{yrbuilt}(tq, yrbuilt), \tag{2.6}$$

where κ are neighborhood fixed effects and g^{sqmt} and $g^{yrbuilt}$ are second-order polynomials that interact time quarter fixed effects with size and year of construction respectively. I then use the predicted values, $\hat{g}_c(x_i, t)$, as an estimate of the property transaction level predicted price dispersion.

Cross-sectional variation. The objective of the empirical analysis in this paper is to investigate whether expected price dispersion can predict prices and returns in the housing market, taking into account property characteristics. Consequently, the challenge in this context lies in the potential correlation between predicted dispersion and property characteristics that can impact transaction prices. To address this challenge, the analysis will involve comparing contemporaneous transaction prices of properties that are similar in size, age, and location but differ in terms of their predicted dispersion. To clarify, this section of the paper focuses on exploring the cross-sectional variation in the data. This approach differs from most asset pricing settings, which concentrate on more liquid asset classes. In the context of housing markets, analyzing the time variation of different properties is often impractical because each property is typically sold only every few years, and properties vary significantly in their holding periods. Since the measure of predicted dispersion will be derived from estimated coefficients, the empirical results in this section will rely on two-stage least-squares (2SLS) regressions, in which :

$$\text{Stage 1:} \quad u^2_{i,tq} = g_c(X_i, tq) + B_X X_i + \eta_{tm} + \kappa_{n,tq} + e_{i,tq} \tag{2.7}$$

$$\text{Stage 2:} \quad y_{i,tq} = \gamma \hat{u}^2_{i,tq} + B_X X_i + \eta_{tm} + \kappa_{n,tq} + \epsilon_{i,tq}, \tag{2.8}$$

where X_i is a vector of property characteristics that include size and age, κ_{nt} are year-quarter fixed effects and μ_{dt} are year-neighborhood fixed effects. The dependent variable $y_{i,tq}$ can refer to the transaction price, the net rent at the time of the transaction or the rental yield.[14]

Alternative identification. To further reinforce identification, I will also instrument the price dispersion using measures of market thickness at the property level that do not directly depend on property characteristics. As demonstrated in various theoretical and empirical papers, thicker markets tend to exhibit less price dispersion (e.g. Gavazza, 2011; Sagi, 2021). Extending this concept to housing markets, I create two measures of market liquidity at the property-transaction level to predict price dispersion. The proposed instruments are based on the premise that each property may potentially have its own market. Given the nature of the data I am working with, these measures will primarily capture sellers' market liquidity. However, we anticipate that general equilibrium factors will influence both sellers' and buyers' market liquidity, resulting in a high degree of correlation

14. Please note that all regression output results presented in this paper will display standard errors that have been adjusted for the use of an estimated regressor in the second stage, achieved through the utilization of a sandwich variance estimator.

between these two measures across different properties and over time.

Following Jiang and Zhang (2022), I build an instrument based on the distance of the properties' *i* characteristics to the mean characteristics of the properties' sold in the same city and within the same year. This measure captures the degree of thinness in the local property market for property *i*. For instance, there will be less suply and demand for an old and large apartment in a city predominantly composed of new and small apartments. The instrument is then built as:

$$Z_{it}^m = (X_{it}^m - \bar{X}_{ct}^m)^2, \ \forall m \in \{size, age, location\}, \tag{2.9}$$

where *size* measures the living area of the apartment in square meters, *age* is the building year of the apartment and *location* is the geographical location of the apartment given by its latitude and longitude. The instrument for location measures the distance between properties' *i* latitude and longitude and the average latitude and longitude of all the properties being sold within the city in year *t*. Given that distances for size, age and location are all measured in different units, the distances are all standardized to have mean 0 and standard deviation of 1 for each year *t*.

In addition, I construct a market thickness measure based directly on the relative frequency of specific combinations of apartment characteristics. The aim is to capture how often a particular combination of characteristics appears on the market at a given point in time. Typical combinations of characteristics will appear more frequently on the market, indicating a higher supply and demand for those specific characteristics. To achieve this, I divide the distribution of size, age, and location into eight equally sized bins for the entire sample. Then, for each year *t*, I calculate the relative frequency of each bin by dividing the total number of transacted properties with those specific characteristics by the total number of transactions in that year:

$$Z_{it}^m = \frac{\#obs_{it}}{\#obs_t}, \ \forall m \in \{size, age, location\} \tag{2.10}$$

I perform two-stage least squares regressions in which observed idiosyncratic price dispersion is instrumented by the measures of market liquidity for the different property characteristics, Z_i^m. By introducing the instruments separately for each characteristic, I am enabling each characteristic's illiquidity to have a distinct impact on the price dispersion.

Time-series variation. Housing differs from more liquid asset classes in that houses are transacted very infrequently. Consequently, the transaction price of a house is not observed every period. To analyze the time-series variation in the measure of predicted dispersion, I employ a portfolio sorting analysis, where I sort transactions into specific portfolios each period based on the level of predicted dispersion in the apartment transactions. I then utilize fixed-effects panel regression methods to estimate the impact of predicted dispersion on expected returns.

I first sort all transactions into equal-sized portfolios based on their predicted dispersion $\hat{\sigma}_{it}$ every quarter. Given the size of the sample I first construct six equally sized portfolios. For each one of the p portfolios I estimate total quarterly housing returns as the sum of capital gains and rental returns:

$$\text{Total housing return}_{p,tq} = \underbrace{\frac{P_{p,tq} - P_{p,tq-1}}{P_{p,tq-1}}}_{\textbf{Capital Gain}} + \underbrace{\frac{R_{p,tq}(1 - c_{tq})}{P_{p,tq-1}}}_{\textbf{Net Rent Return}} \tag{2.11}$$

where $P_{p,tq}$ is the hedonic transaction price in portfolio p in quarter tq, $R_{p,tq}$ is the hedonic rental payment and c_{tq} are utility, maintenance and vacancy costs as a share of the rent. To estimate the value of the hedonic price and the hedonic rental return, I employ rolling window time-dummy hedonic methods, which ensure that fluctuations in the return series are not driven by changes in the sample of transactions sold over time. Based on the transactions assigned to each portfolios, I first build rolling-window time-dummy hedonic housing price indices for each portfolio.[15] Based on these hedonic indices, I build quarterly capital gains series. Using the individual rental yields data constructed based on the *Mietspiegel* data, I then build rental yield rolling-window time-dummy time-dummy hedonic indices for each portfolio, which I benchmark to the mean portfolio rental yield in last period to have a time-series of rental yields for each portfolio. For more details on the construction of the return series please refer to Appendix 2.E. All returns are then transformed into log points, to be more robust to outliers (Bali, Engle, and Murray, 2016).

To assess the impact of predicted price dispersion on housing returns, I conduct the following fixed-effects panel regression:

$$y_{p,tq} = \beta_0 + \gamma \hat{u}_{p,tq} + B_X X_{p,tq} + \eta_{tq} + \epsilon_{p,tq}, \tag{2.12}$$

15. For an overview of hedonic pricing methods in the context of housing markets, please refer to Hill (2013).

where the dependent variable $y_{p,tq}$ is one of the outcomes of interest (total returns, excess returns, capital gains, rental yields) for portfolio p in year-quarter tq. $\hat{u}_{p,tq}$ is the average predicted dispersion in portfolio p and $X_{p,tq}$ is a vector of the average characteristics of the transactions that compose portfolio p and η_{tq} are time fixed-effects.

2.4 Empirical results

In this section, I test the model predictions outlined in Section 2. Using the transaction level data, I exploit within neighborhood-year variation to assess the relationship between predicted price dispersion and transaction prices, as well as rents. I show a significant negative effect on transaction prices, which is notably less pronounced in the case of rents. Subsequently, I proceed to evaluate the impact of predicted price dispersion on rental yields, capital gains, and total returns. I identify a clear positive relationship with rental yields, no discernible pattern concerning capital gains, and as a result, a strong positive correlation with total returns.

Shifting the focus to across-portfolio variation, I demonstrate that portfolios with higher levels of predicted dispersion significantly outperform others in terms of housing returns, reinforcing the findings at the property transaction level. Moreover, the analysis reveals that the premium associated with investing in higher predicted dispersion portfolios varies over time, increasing during market downturns.

2.4.1 Transaction level data

Predicted dispersion, transaction prices and rents. To better understand the effects of price uncertainty on net rental values and transaction prices, I conduct 2SLS regressions as in (2.7) for each city separately, where the outcome variables are transaction prices and rents net of utilities and maintenance costs.[16] To ensure comparability between the results of prices and net rents, I initially standardize the variables to have a mean of zero and a standard deviation of one. Figure 2.1 illustrates a bin scatter plot based on the regression results, showing both transaction prices and rents by city. A discernible pattern emerges across all cities in the sample. While transaction prices are significantly lower for higher levels of predicted price dispersion, rents largely remain constant across the distribution of price dispersion.

The tables in Appendix 2.F present the 2SLS regression output underlying the binned scatter plots. They confirm that the coefficient of predicted price dispersion

16. I employ the net rents value to ensure that our results are not influenced by variations in utility costs.

on transaction prices is two to three times larger than the one on net rents. Additionally, the coefficient on net rents is for some cities statistically insignificant, indicating that apartments with higher predicted price dispersion are not rented out at lower levels of rent. The effect of predicted price dispersion on transaction prices is not only highly statistically significant, with all cities displaying coefficients significant at the 1% level, but it is also economically relevant. Controlling for property size, age, neighborhood, and the year quarter of sale, the data suggests that moving from the first to the fifth quintile of predicted price dispersion distribution results in a decrease in sales prices ranging from 7,000€ (in Cologne) to 10,000€ (in Berlin). In other words, apartments sold in the same neighborhood and in the same year-quarter with similar characteristics, on average, will display differences in prices that amount between 4% and 7% of the average sales price in their respective cities.[17]

As a robustness test, I replicate the same analysis as described above but limit the dataset to include only those observations for which both price and rent information is available. This targeted focus on a subset of observations serves to alleviate potential biases that may arise from the data matching process discussed in Section 3 of this paper. The results are presented in Appendix 2.F.2. The regressions conducted on this subset of observations corroborate the findings obtained from the main sample.

Furthermore, I show that price uncertainty also affects the second moment of the distribution of transaction prices. Properties characterized by higher price uncertainty exhibit prices with a greater standard deviation. The detailed results can be found in the appendix 2.H. This highlights that the observed discount in transaction prices, which I am quantifying, is due to uncertainty rather than solely from lower demand for this category of properties. While lower demand may account for the lower transaction prices of these properties, it does not explain the increased volatility in transaction prices.

Predicted dispersion and returns to housing. As illustrated in Figure 2.1, the effect of price dispersion on transaction prices is notably stronger than its effect on rental values. To understand whether this translates into a positive effect of price uncertainty on rental yields, I perform 2SLS regressions as in Equation (2.7), using rental yields at the point of sale as the outcome variable. Based on the regression results, I create binned scatterplots for each city in my sample, which are displayed in Figure 2.2. The regression output for each city can be found in the tables in Appendix 2.I. In all cities, there exists a clear positive and significant relationship between predicted dispersion and rental yields. The effects are not only statistically highly significant but also economically significant. When comparing sales of apart-

17. These results are obtained by running regression (2.7) for each city separately and including a categorical variable for the quintiles of the idiosyncratic price uncertainty distribution.

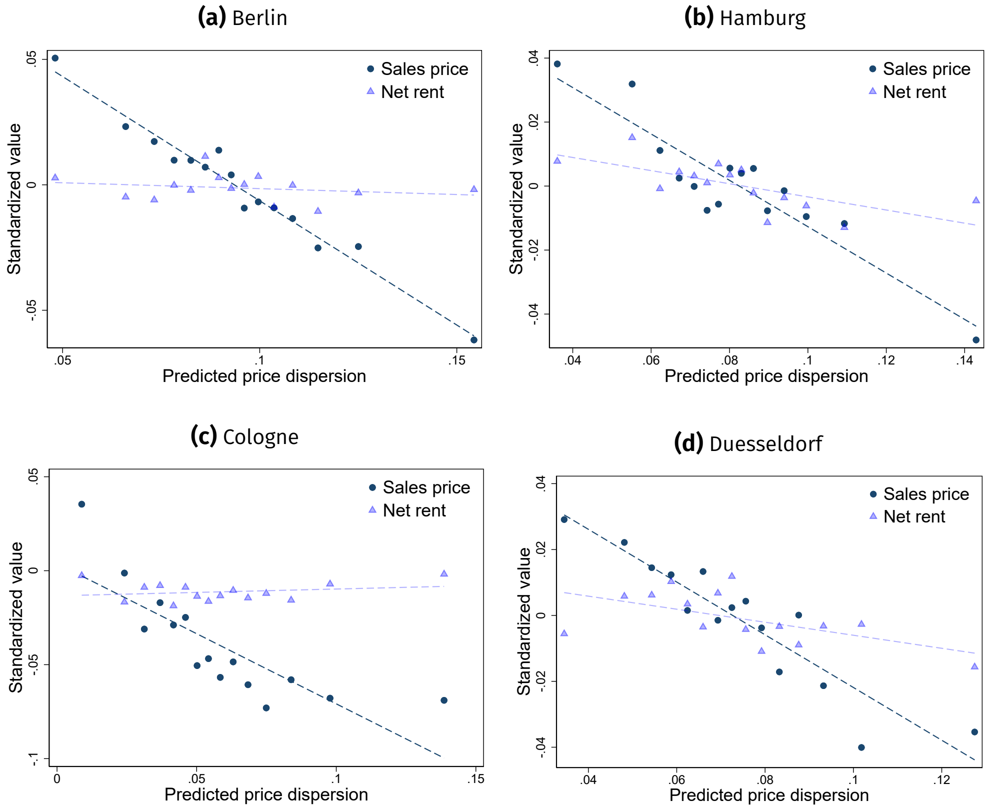

Figure 2.1. Predicted price dispersion, sales prices and net rents

Note: All panels display bin scatters with 15 bins. Each bin represents the average value of sales prices and net rents residualized based on regression (2.7). Both sales prices and rents are standardized to haven mean zero and standard deviation of one.

ments within the same neighborhood in the same year quarter and controlling for size and building age, moving from the lowest to the highest quintile of predicted dispersion predicts, on average, an increase of between 20 (Dusseldorf) to 34 (Hamburg) basis points in the rental yield. This constitutes a substantial effect, as it represents between 4% (Dusseldorf) to 8.5% (Hamburg) of the average rental yield in the respective cities over the time period covered in the sample. This result also holds for the subsample, in which both prices and rents are observed at the point of sale as shown in Appendix 2.I.1.

Next, I analyze the relationship between price uncertainty and capital gains, as well as total returns. The objective is to determine whether the predicted dispersion at the point of sale can serve as a predictor of future capital gains or total returns. Using the detailed information on the precise location of the apartments within the building, I match transactions of the same apartment over time, allowing me to construct apartment-level capital gains.[18] By utilizing the rental yield values at the point of the first sale, I subsequently calculate the average yearly total return for each pair of transactions involving the same apartment. Unlike rental yields, capital gains and total returns are observed only over the holding period and not for each transaction. Therefore, the unit of observation is now pairs of apartment sales and re-sales. Since the holding period is not observed at the time of the first sale, I cannot use the 2SLS framework as in Equation (2.7). Instead, I employ a two-step estimator in which I additionally control for the length of the holding period in the second stage. To be specific, I include a categorical variable that divides the holding period into 10 equally sized categories. First, I run the same first-stage regression at the apartment transaction level as outlined in Equation (2.7). Then, in the second stage, I regress the outcome variable for each pair of sales (j) on the predicted dispersion of the first sale, while controlling for property characteristics, time and neighborhood fixed effects, and the length of the holding period ($hp_{i,j}$) between the sale and re-sale.

$$\text{Stage 1:} \quad u^2_{i,tq} = g_c(X_i, tq) + B_X X_i + \eta_{tm} + \kappa_{n,ty} + e_{i,tq} \tag{2.13}$$

$$\text{Stage 2:} \quad y_{i,j} = \gamma \hat{u}^2_{i,tq} + B_X X_i + \eta_{tm} + \kappa_{n,ty} + \beta hp_{i,j} + \epsilon_{i,tq}, \tag{2.14}$$

where X_i is a vector of property characteristics that include size and age, η_{tq} are year-quarter fixed effects and $\kappa_{n,ty}$ are year-neighborhood fixed effects. The dependent variable y_{it} can refer to the capital gains and total returns.

I present the results in the form of binned scatterplots in Figure 2.2. Predicted price dispersion at the point of the first sale does not appear to be a reliable predictor of capital gains. Across all cities, no robust relationship is evident, and the coefficient on predicted dispersion is consistently statistically insignificant. This finding aligns with existing evidence regarding idiosyncratic risk in housing markets, which indicates that idiosyncratic price risk predominantly materializes at the points of sale and re-sale, thus not being attributable to changes in the house's fundamentals over time (Giacoletti, 2021; Sagi, 2021). In other words, we would not anticipate real estate with high predicted dispersion to appreciate at a different rate than real estate with lower price dispersion.

As for total returns, the pattern differs. In this case, I observe a robust and statistically significant positive effect of predicted price dispersion on total returns across

18. Utilizing the information on the length of the holding period, I proceed to annualize the capital gains.

all cities. Controlling for property characteristics, time, and neighborhood fixed effects, properties with higher levels of price uncertainty at the point of the first sale outperform the rest of the market in terms of future total returns. It is important to note that by incorporating property characteristics, time, and location fixed effects, the results demonstrate that these excess returns cannot be attributed to varying exposures to the market portfolio. The regression output for each city can be found in the tables in Appendix 2.I. Similarly, for total returns, the effects are not only statistically highly significant but also economically substantial. When comparing sales of apartments within the same neighborhood in the same year quarter and controlling for size and building age, moving from the lowest to the highest quintile of predicted dispersion predicts, on average, an increase ranging from 40 (Berlin) to 57 basis points (Cologne) in future total returns. This represents a significant impact, accounting for approximately 4% (Berlin) to 6% (Cologne) of the average total return in the respective cities over the time period covered in the sample. Please note that in the case of Hamburg, the number of observations is very limited due to the absence of key information necessary for the identification of repeat-sales.[19] Given this limited dataset, it is not surprising that the effects are not statistically significant. Nevertheless, they consistently exhibit the expected direction.

Predicted dispersion and rental yields for multi-family housing. The model presented in Section 2 characterizes the optimal bid for a housing investor. Typically, large real estate investors hold multi-family houses in their portfolios rather than individual apartments. Furthermore, assuming risk-averse investors who consider resale risk at the time of purchase is even more appropriate for characterizing investment decisions in the multi-family housing market. This is because, in this market, average transaction prices are very high, representing a significant portion of investors' total portfolios. The dataset, constructed by Amaral et al. (2023), also includes information on transactions involving multi-family housing. In this section, I replicate the analysis conducted in the previous sections, but this time utilizing data on multi-family house transactions. To account for specific characteristics of the multi-family housing market, I incorporate additional control variables when measuring price dispersion, such as the building's lot size or the percentage of commercial use of the property.[20] I then employ the same 2SLS approach as in (2.7) to investigate the impact of predicted dispersion on rental yields. For multi-family housing, data on rental income after accounting for maintenance and utilities costs at the point of sale is available for a significant portion of the transactions for the cities of Berlin and Hamburg.[21] Therefore, in this analysis, I only consider observa-

19. For more details, please refer to Appendix 2.C.3.

20. Please note that I exclude all buildings in which commercial properties occupy more than 20% of the usable area of the building.

21. Unfortunately, in the case of Cologne most of the transactions of multi-family housing have missing information about the size of the houses. For Duesseldorf, only information on the gross rental

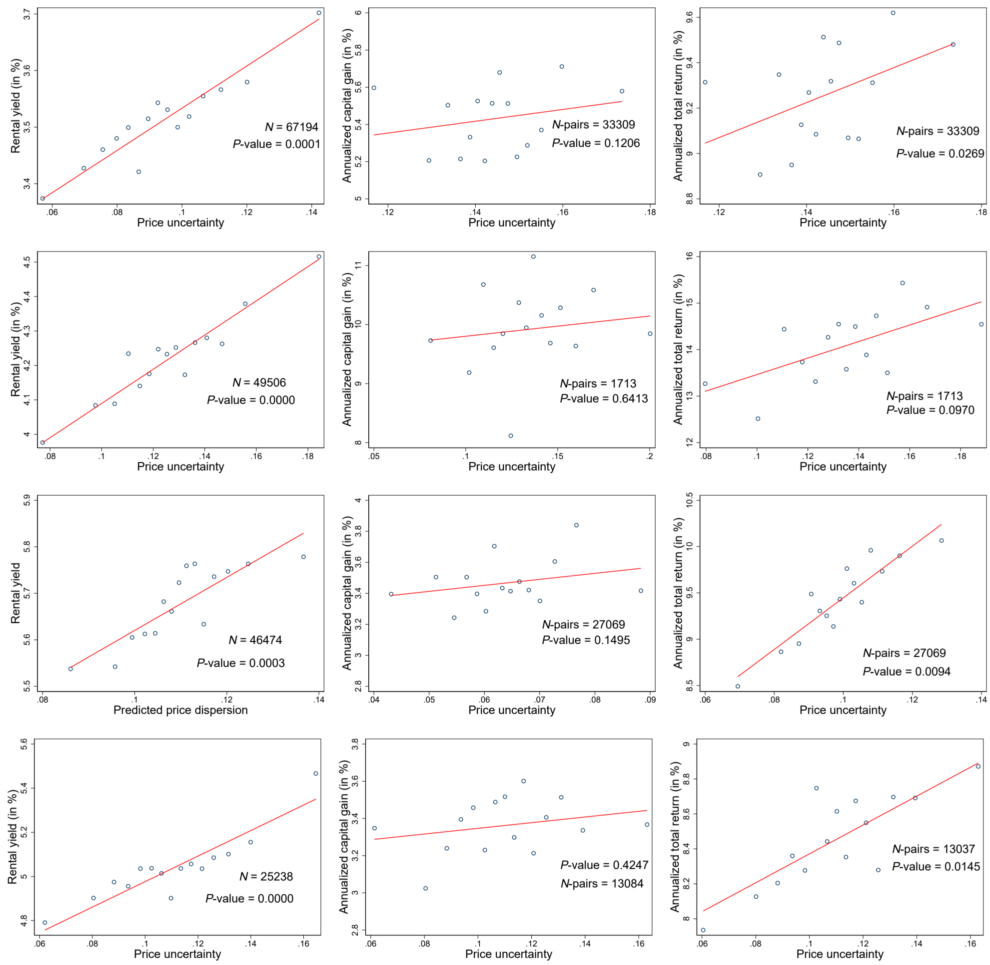

Figure 2.2. Binscatter of housing returns on predicted price dispersion by city

Note: The first column displays a binscatter of rental yields on predicted price dispersion based on the 2SLS regression output of (2.7). Here the unit of observation are transactions. The second and third columns displays a binscatter of capital gains and total returns on the predicted price dispersion at the point of the first sale based on the two-step regression estimator (2.13). Here the units of observation are pairs of sale and re-sale of the same apartment.

tions for which I simultaneously have data on transaction prices and rental incomes.

The results are presented in Figure 2.3. Similar to the findings for apartments, a positive and robust relationship between predicted dispersion and rental yields at the transaction-house level is evident. After accounting for property characteristics, time and location fixed effects, it becomes clear that multi-family houses with higher predicted averages tend to yield higher rental returns on average. Once

yields (before excluding maintenance costs) is available, as such, not allowing for a clear comparison across transactions.

again, the results exhibit not only statistical significance but also considerable economic relevance. Transitioning from the lowest quintile to the top quintile of predicted price dispersion in a given year and neighborhood, while controlling for property characteristics, predicts a rental yield increase of 65 basis points in Berlin and 40 basis points in Hamburg. These increases represent 7% and 6% of the average rental yields observed over the sample period in Berlin and Hamburg, respectively. For detailed regression output tables, please refer to Appendix 2.I.2.

To further test the robustness of these findings, I conducted the same analysis exclusively on multi-family houses without any commercial properties. Commercial properties are often more challenging to value. Importantly, the results remain consistent, indicating that even for 100% residential multi-family housing, rental yields increase with predicted dispersion.

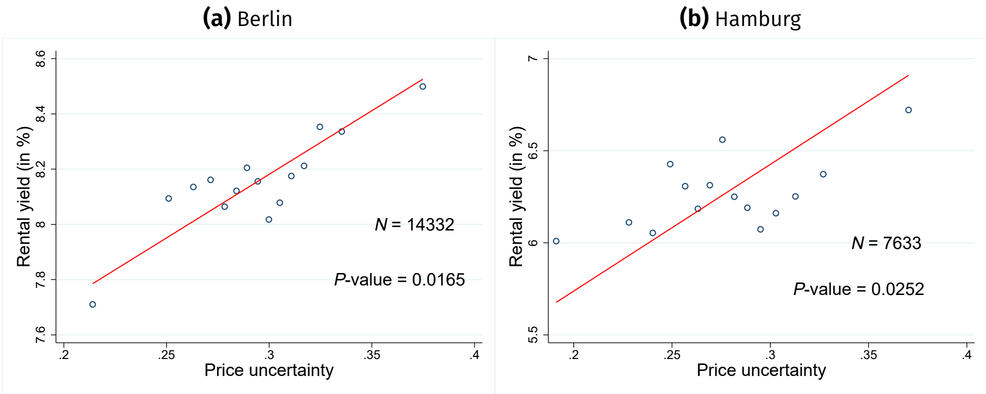

Figure 2.3. Rental yields & predicted dispersion for multi-family housing by city

Note: The binned scatters are based on regression (2.7) with ratio of net rental income to transaction price of multi-family houses at the point of sale as the outcome variable. Panel a) displays the results for Berlin for the period between 1970 and 2022 and Panel b) displays the results for Hamburg for the period between 1991 and 2022. The regression output tables can be found in Appendix 2.I.2.

2.4.2 Portfolio sorting analysis

Properties are traded very infrequently, which means that a time series for the value of a specific property is not observed, and the variation that I can analyze at the transaction level is cross-sectional. Using the portfolio price and return time-series constructed in Section 4.2, I can, however, also analyze the time-series variation. Since these portfolios were built based on hedonic methods that control for property characteristics, the differences in performance across the portfolios arise solely due to their differences in value uncertainty. From this perspective, the hedonic portfolio sorting analysis can be interpreted as a multi-sort portfolio analysis, where researchers aim to control for specific asset characteristics to isolate the effects of the risk factor (Bali, Engle, and Murray, 2016). In this section, I first demonstrate that portfolios containing properties with higher levels of uncertainty outperform the rest of the market. Decomposing the total returns, I then illustrate that the return differences across portfolios stem from variations in rental returns and not from capital gains. This corroborates the results from the transaction-level analysis. Finally, I also establish that exposure to the market portfolio remains constant across the portfolios, and higher value uncertainty portfolios exhibit higher alphas.

In Figure 2.4, I plot the total nominal returns by portfolio for each city over the entire sample period, accompanied by the 95% confidence intervals. The portfolios are sorted based on the level of predicted dispersion associated with the transaction of the properties within them. Portfolio 1 consists of transactions of properties with the lowest levels of predicted dispersion, whereas portfolio 6 comprises transactions of properties with the highest levels of predicted dispersion. All three cities exhibit a consistent pattern: total returns consistently rise with increasing value uncertainty, demonstrating a nearly monotonic relationship.

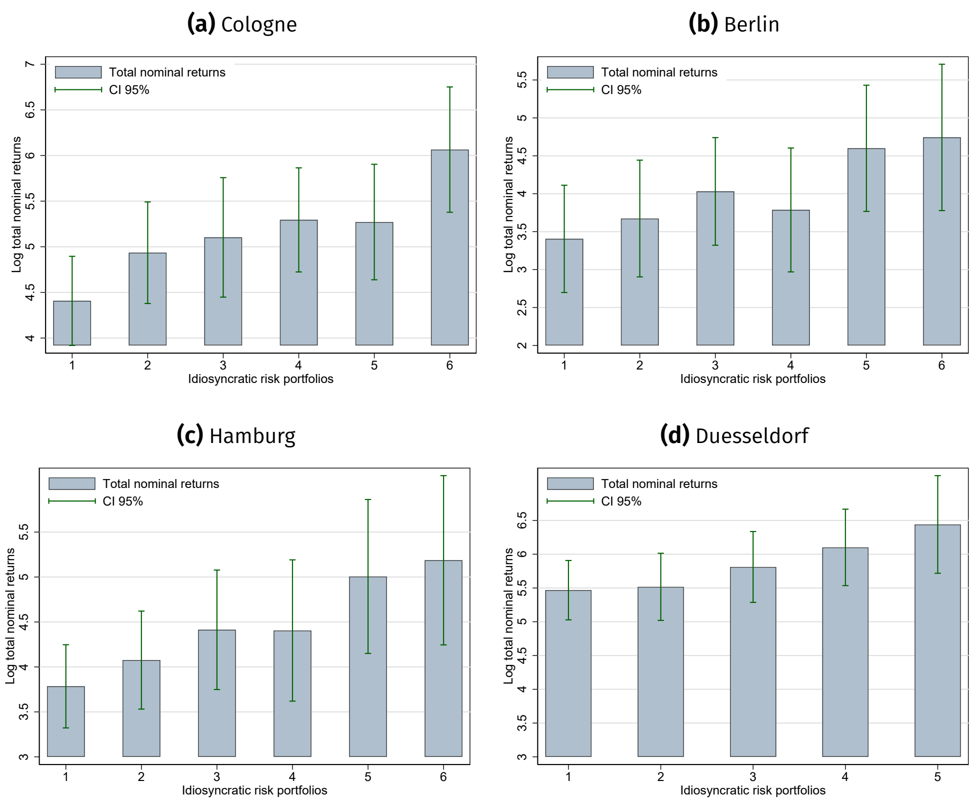

Figure 2.4. Log total nominal returns & predicted dispersion by city

Note: The Figure shows the total nominal returns on six equally-sized portfolios built based on predicted disperion quantiles. The returns to the portfolios are constructed using hedonic regressions controlling for property characteristics. For more details please refer to section 2.3.2

To assess the magnitude of the return differences depicted in Figure 2.4, I conduct hypothesis tests to determine if these differences are statistically significant. Following the best practices in the asset-pricing literature, I test the differences in log excess returns. I build the excess returns by subtracting the returns on short-term German government bonds. Additionally, I perform a decomposition of the return differences into separate components, namely capital gains and rental return differences. The results can be found in Table 2.3, where I provide the average log excess return difference between portfolio 6 and portfolio 1 as well as the difference between portfolio 6 and the average of the rest of the portfolios for the all cities separately.

For all cities, investing in portfolio 6 provides a statistically significantly higher return than investing in portfolio 1. For example, for Cologne investing in the portfolio with the highest value uncertainty provides a premium of 149 basis points per quarter over investing the portfolio with the lowest value uncertainty. Not only is this premium statistically significant, but it also economically very large. The most documented investment risk strategies in the stock market literature, such as the small-minus-big, high-minus-low or momentum strategies yield a return premium in the range of 100 to 150 basis points per quarter (e.g. Fama and French, 2015; Ehsani and Linnainmaa, 2022). The differences in returns between portfolio 6 and an average of the rest of the portfolios is also statistically significant, although not as large as the difference to portfolio 1.

The second and the third column also show the differences in capital gains and rental returns. It becomes evident that most of the return differences come from the differences in rental returns and not from the differences in capital gains. This result is consistent with the predictions of the model and the transaction-level results, that also indicated that rental returns and not capital gains increase with value uncertainty.

Exposure to systematic risk. Although the differences in total returns are quite large, this does not necessarily mean that varying levels of value uncertainty are driving the return differences. It could be the case that the different portfolios have different exposures to systematic risk in the market. In order to test this hypothesis, I run the following regression:

$$ln(r_{pt}) = \alpha_p + \beta_p ln(r_{mt}) + \epsilon_{pt}, \tag{2.15}$$

where $ln(r_{pt})$ is the log total excess return for portfolio p, which is constructed by subtracting the risk-free return to the nominal total return of each portfolio, and $ln(r_{mt})$ is the total excess return for the city of Cologne. In Figure 2.5 I plot the both the α coefficient for each portfolio p, as well as the β coefficient. While the alphas show the exact same pattern as the total nominal returns, the betas do not show

Table 2.3. Portfolio return differences in log points by city

		Cologne		
Portfolio	Excess Returns	Capital Gains	Rent Returns	N
P6 vs P1	1.55*** (0.29)	-0.00 (0.27)	1.39*** (0.07)	264
P6 vs rest	1.28*** (0.27)	-0.03 (0.25)	1.15** (0.56)	792
		Berlin		
Portfolio	Excess Returns	Capital Gains	Rent Returns	N
P6 vs P1	1.06** (0.44)	0.45 (0.44)	0.61*** (0.14)	214
P6 vs rest	0.84** (0.35)	0.36 (0.34)	0.47 (0.43)	642
		Hamburg		
Portfolio	Excess Returns	Capital Gains	Rent Returns	N
P6 vs P1	1.47*** (0.47)	0.32 (0.40)	1.14*** (0.20)	166
P6 vs rest	0.84*** (0.32)	0.33*** (0.03)	0.51* (0.29)	498
		Duesseldorf		
Portfolio	Excess Returns	Capital Gains	Rent Returns	N
P5 vs P1	0.70*** (0.26)	0.04 (0.22)	0.64*** (0.15)	306
P5 vs rest	0.45** (0.22)	0.08 (0.17)	0.37 (0.79)	765

Note: Differences are measured as coefficients in a random effects panel regression of the dependent variable (log capital gain, log rental yield and log total housing return respectively) on a P6 dummy and year fixed effects. Driscoll-Kraay standard errors (in parenthesis). $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

significant differences across the portfolios. This indicates that the observed differences in portfolio total nominal returns are not being driven by differential exposure to the market portfolio returns. To the extent that the market portfolio returns represent systematic, non-diversifiable, risk, this indicates that the main results are not driven by different exposures to systematic risk.

(a) alpha **(b)** market beta

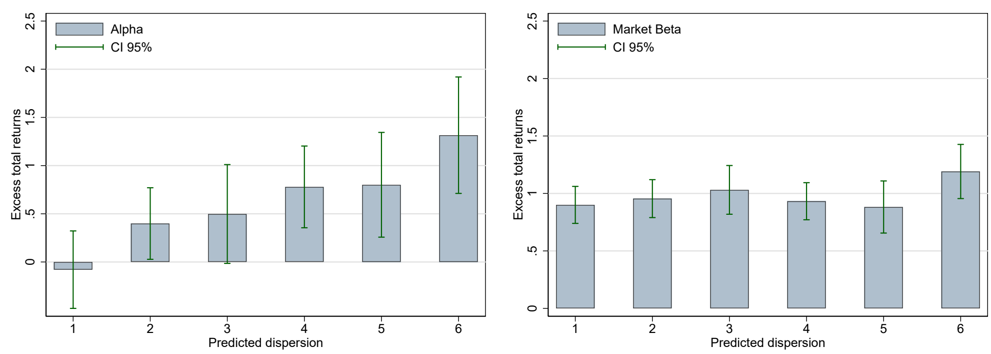

Figure 2.5. Total returns controlling for systematic risk exposure, Cologne 1989-2022

Note: The six equally-sized portfolios are built on the predicted dispersion. Standard errors are adjusted for time-series autocorrelation using Newey-West with 6 quarter lags.

2.4.3 Robustness analysis

In this section, I present the robustness analysis conducted to ensure that alternative factors are not influencing the primary results of the paper. Here, I specifically emphasize demonstrating the robustness of the findings that confirm the three main predictions of the model about properties with higher value uncertainty: i) they trade, on average, for lower prices, ii) they yield, on average, higher rental yields and iii) they do not realize, on average, higher capital gains but have higher total returns.

Observed rental income and price at transaction level. The main results, both at the transaction-level and in the portfolio-sorting analysis, are based on a matched sample of transactions where I align transaction prices with net rental income from the *Mietspiegel*, as explained in the data section. This approach introduces two potential sources of bias. Firstly, it's not certain whether all the properties I match are actually being rented, raising questions about the accuracy of predicting the rental income these properties would generate if they were indeed in the rental market. Secondly, the matching process relies on the same set of characteristics used to predict price dispersion. If I do not find an effect when regressing rental values on predicted price dispersion, it could potentially invalidate the rest of my results.

To address these concerns, I replicate all my analyses using only the sample of properties for which I simultaneously observe rental income and transaction prices. I conduct this analysis for both apartments and multi-family housing. This approach addresses both concerns, as the presence of information on rental income guarantees that the property is indeed being rented out and provides the exact level of rental income, eliminating the need for estimation. As I demonstrate in Appendices 2.F.2 and 2.I.1, all results hold when using the samples for which both rental income and prices are observed, with the results being particularly robust in the case of multi-family housing.

All sales. As mentioned in Section 2.3, the inclusion of apartment fixed effects in my baseline regression could pose two problems. Firstly, considering that properties are rarely transacted during the sample period, the limited number of observations per fixed effect has the potential to introduce bias to the coefficients and consequently impact the estimated residuals in my baseline regression (2.1). Secondly, properties that transact more than once might not be representative of the universe of property transactions and have special characteristics that might bias the results (Haan and Diewert, 2011). In order to assess whether these issues might be influencing my results, I conducted a new analysis where I excluded the apartment fixed effects from the baseline regression and using the exact same sample, I run the following regression:

$$ln(p_{i,tq}) = \eta_{tm} + \kappa_{n,tq} + f_c(x_i, ty) + u_{i,tq}, \tag{2.16}$$

which is equal to the regression (2.1), but excludes the property fixed effects. Compared to my baseline results, the regression without apartment fixed-effects yields significantly greater dispersion in the residuals. However, the residuals from the specification without apartment fixed-effects exhibit a strong positive correlation with the residuals from the specification with apartment fixed-effects. Therefore, it is unsurprising that I am able to replicate the main results. I present the detailed results in Appendix 2.J.1. Summary statistics for all sales by city can be found in Table 2.C.1 in the Appendix.

Housing renovations and price dispersion. The model specification in equation (2.1) does not take into account the potential impact of renovations on the value of apartments. Without explicitly controlling for renovations, it is possible that the residuals are picking up this effect. Therefore, the model may not be capturing a measure of idiosyncratic price deviation, but rather a measure of the enhancing value of renovations. Additionally, apartments continuously depreciate, which counteracts the effects of renovation. To determine whether these two effects are a significant source of measurement error in my analysis, I adapt (2.1) by including building-time fixed effects. Since the largest renovation works are typically done simultaneously for all apartments within a building, this approach should already control for the most significant renovation works. To estimate the idiosyncratic price deviations, I use the following regression:

$$ln(P_{i,tq}) = b_{i,ty} + \eta_{tm} + \kappa_{n,tq} + fc(x_i, ty) + u_{i,tq}, \tag{2.17}$$

where $b_{i,ty}$ is a building-year fixed effect that captures building specific characteristics that also change over time. Given the large number of buildings for which there are several apartment transactions every year, I am able to estimate the coefficients precisely. As I show in Appendix 2.J.3 controlling for building renovations does not change my results.

Adjusting for heterogeneity in holding periods. Equation (2.1) does not explicitly take into account the relation between the variance of the residuals and holding period. Giacoletti (2021) shows that the variance of the residuals increases slightly with holding period. Additionally, the properties, which are sold more often will have smaller residuals by construction, since the apartment fixed-effects in equation (2.1) will be better estimated. To take these issues into account, I add a second step to the estimation of the transaction level price dispersion, in which I explicitly regress the squared residuals from equation (2.1) on a smooth function of the holding period, hp_i, interacted with the number of sales, $sales_i$:

$$u_{i,tq}^2 = g_c(sales_i, hp_i) + e_{i,tq}^2. \tag{2.18}$$

Then I take $e_{i,t}^2$ as my new measure of the price dispersion. I then follow the same steps as described in Section 3 of the paper and analyse the relation between prices and returns and the new measure of predicted price dispersion that explicitly takes into account the relation between the squared residuals from regression (2.1) and the length of holding period as well as the number of times the property was transacted. As shown in Appendix 2.J.4, all the main results hold.

Instrumenting price uncertainty. In my baseline analysis, I regress realized variance of the pricing errors on property characteristics to generate a prediction of price uncertainty. This process inherently creates a correlation between the measure of ex-ante price uncertainty and the property characteristics. This correlation could potentially raise concerns about the main results of the paper, as I might be capturing a mechanical effect related to a preference for specific types of characteristics in transaction prices.

To address this issue, I employ direct measures of sellers' market thickness to predict price uncertainty. The first measure is based on the Euclidean distance between property characteristics and the mean characteristic in the market. The second measure relies on the relative frequency of specific characteristics in the market. Detailed information on the construction of these measures can be found in Section 4.2. As demonstrated in Appendix 2.J.2, using these measures of market thickness to predict price dispersion does not alter the main results and, in some cases, even reinforces them. These results are also confirmed in the following section, where I show a strong correlation between measures of market size and liquidity and value uncertainty at the transaction property level.

Bargaining power and transaction prices. One of the predictions of my bargaining model in section 2.5 is that a higher bargaining power of the buyer could explain my empirical results. Intuitively, if properties with higher price uncertainty have thinner buyer markets, then we would expect buyers to have higher bargaining power, consequently driving down the prices of these properties. To test this hypothesis, I approximate the number of potential buyers per house by using click data from online advertisements. Specifically, I construct two measures of buyer market thickness using information on the number of clicks per ad and the number of times the seller is contacted per ad. While clicking on an ad does not necessarily indicate an intent to buy and is thus a noisy proxy for potential demand, contacting the seller of the property involves writing a text and clearly demonstrates an interest in acquiring the property. I then regress price uncertainty on these two proxies of buyer market thickness at the property-transaction level. Additionally, I include property characteristics, location, and time fixed effects to ensure a comparison of similar properties. The results for the city of Cologne are displayed in Figure 2.6. There is no significant relationship between price uncertainty and buyer market thickness for both proxies. Indeed, the data does not indicate that properties with higher price uncertainty are transacted in thinner buyer markets.

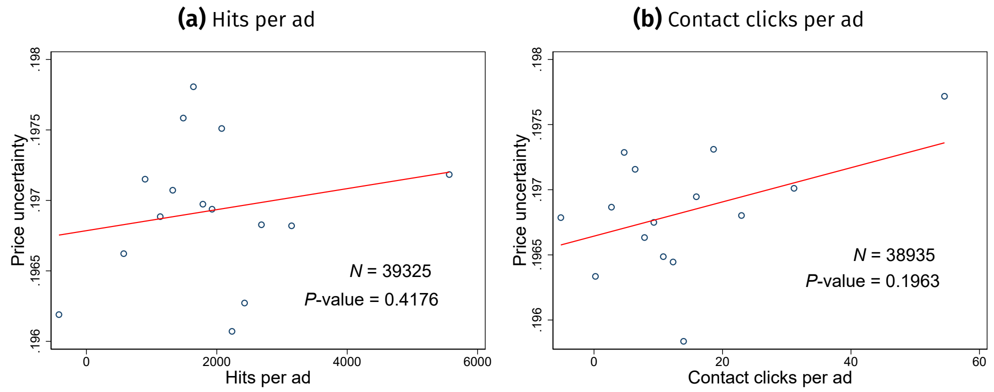

Figure 2.6. Price uncertainty and buyers' bargaining power

Notes: Panel (a): Binscatter showing the relation between price uncertainty and measures of buyers' bargaining power. The output is based on regressions controlling for time and location fixed effects, property characteristics and time on the market. The data is for the city of Cologne and covers the period between 2008 and 2018. The source is Immoscout.

Additionally, bargaining power is not only affected by number of potential buyers, but also by the outside options of the buyers. As I show in Section 2.6, properties with higher price uncertainty have a lower number of comparable properties on the market. This means that buyers wanting to buy these properties will typically face a lower number of outside options in the market. All else constant, this increases the bargaining power of sellers, which can then raise prices even more. And, as such, this would go against ma empirical findings of a pricing discount for properties with higher price uncertainty.

Overall, I do not find evidence that higher buyers' bargaining power is driving my empirical results. Theoretically, it is also not clear that buyers will have a higher bargaining power for properties with higher price uncertainty, as the number of outside options is typically smaller for this type of properties.

2.5 Theoretical Framework

Houses are highly heterogeneous goods, and their characteristics are valued differently by potential buyers. For instance, larger houses tend to be more appealing to larger households. Consequently, houses located in close proximity to one another may be traded in markets characterized by distinct types and quantities of potential buyers, exposing them to markets with varying sizes and thicknesses. Intuitively the size and the thickness of the markets will affect the quality of the matching process between sellers and buyers. Thinner markets typically result in less efficient matching between sellers and buyers, thereby generating greater uncertainty surrounding transaction prices.[22]

Additionally, the attributes that render a house attractive for purchase also influence its demand in the rental market. This, in turn, impacts the uncertainty surrounding the rental value at which the property can be rented out. In this section, I develop a theoretical framework to characterise the optimal bid for a risk-averse investor who faces uncertainty regarding both the rental and resale values of the property.

Setup. This is a model with three periods, with one seller and one financially unconstrained investor, who wants to buy a house to rent it out. In the first period, the seller puts the house for sale and enters a Nash bargaining process with the investor. The bargaining power of the investor is given by α. The α parameter can be understood as reflecting the buyers' market thickness for the specific house h.[23] After having bought the house in the first period, the investor rents it out in the second period. The rent is exogenous and random. In the third and final period, the investor sells the house for a random price. I assume that, in the first period, the investor knows the reservation value of the seller, $\underline{PV_S}(h)$, and, as such, will not bid below it. The bargaining problem of the first period can then be written as:

$$\max_{V_B, V_S} \quad V_B^{\alpha} V_S^{1-\alpha} \tag{2.19}$$

$$s.t. \quad V = V_B + V_S \tag{2.20}$$

$$V = PV_B(h) - \underline{PV_S}(h) \tag{2.21}$$

$$\alpha \in (0,1) \tag{2.22}$$

where the first constraint is the standard constraint from a Nash bargaining problem that splits the bargaining surplus among the seller and the buyer. The second constraint tells us that the value that will be split between buyer and seller equals the difference between the private valuation of house h by the buyer, PV_B, and the reservation value of the seller, $\underline{PV_S}$. In other words, the final transaction price will be between the private valuation of the buyer and the reservation value of the seller and will be determined by the relative bargaining power of each party. For simplification, I assume that housing is the only asset in the economy and, as such, all income generated by housing will be consumed. The private value of the

22. This is because, all else being equal, the probability of a match occurring between a seller and a buyer who value the house equally is lower in thinner markets (e.g Han and Strange, 2015).

23. I take the relation between bargaining power and number of buyers as exogenous, however it can be micro-founded in a setting of sequential bargaining as demonstrated in Rubinstein and Wolinsky (1985).

investor of house h is the discounted value of renting out the house in period 2 for R_2 and selling it in period 3 for the expected price $P_3(h)$:

$$PV_B = \beta E_1[u_2(R_2(h)] + \beta^2 E_1[u_3(P_3(h))], \tag{2.23}$$

where P_3 and R_2 are log-normally distributed with means μ_P and μ_R and variances σ_P^2 and σ_R^2, respectively. $\beta \in (0,1)$ is the discount factor. The mean μ_P can be thought of as the expected market value of the property, while the variance σ_P^2 measures the house-specific price deviation from its expected market value. The same logic holds for the rent. This model describes transactions for one specific house on the market. When the investor rents out the house and resells it, they face a larger market and receive a random rent and price.[24] Furthermore, I assume that the risk-averse buyer has CRRA utility.[25]

Solution. To solve the maximization problem, I substitute the Nash bargaining constraint into the problem:

$$\max_{V_S} \quad (V - V_S)^{\alpha} V_S^{1-\alpha} \tag{2.24}$$

$$s.t. \quad V = PV_B(h) - \underline{PV}_S(h) \tag{2.25}$$

$$\alpha \in (0,1). \tag{2.26}$$

Deriving the first-order condition and solving for V, we get:

$$V = \frac{1}{(1-\alpha)} V_S. \tag{2.27}$$

Plugging in the constraint and using the definition of the private value of the investor yields:

$$\frac{1}{(1-\alpha)} V_S = \beta E_1[u_2(R_2(h))] + \beta^2 E_1[u_3(P_3(h))] - \underline{PV}_S(h). \tag{2.28}$$

Since the rent in period 2 and the price in period 3 are log-normally distributed, we have that:

$$E_1[ln(P_3)] = ln(E_1[P_3]) - \frac{1}{2} Var_1[ln(P_3)] \tag{2.29}$$

$$E_1[ln(R_2)] = ln(E_1[R_2]) - \frac{1}{2} Var_1[ln(R_2)] \tag{2.30}$$

24. The randomness of both sale and rent prices can be justified by extensive empirical evidence demonstrating the substantial unpredictability of prices in housing markets (Giacoletti, 2021; Kotova and Zhang, 2021).

25. For simplification, I assume log utility.

Given that the buyer knows the reservation value of the seller, the optimal bid of the buyer in the first period will equal the bargaining surplus of the seller, $B^* = V_S$. As such, assuming the buyer has log utility, we have the following expression for optimal bid by the buyer in period 1:

$$B^* = V_S = (1-\alpha)\left[\beta(ln(\mu_R) - \frac{1}{2}\sigma_R^2) + \beta^2(ln(\mu_P) - \frac{1}{2}\sigma_P^2) - \underline{PV_S}(h)\right] \quad (2.31)$$

Since the optimal bid of the buyer will be at or above the reservation value of the seller, the bid will be accepted. I do not explicitly model the sellers' problem, however, ss demonstrated in DeGroot (2005) and under the assumption that the seller knows the distribution of buyers, it is optimal for sellers to accept the first bid above their reservation value.

2.5.1 Comparative statics

In this subsection, I explore the comparative statics of the models' equilibrium predictions, primarily based on equation (2.31). In doing so, I investigate the effects of price and rental dispersion, as measured by the idiosyncratic variances, on transaction prices and returns to housing. These predictions are then tested empirically in the following sections of the paper.

P1. Higher idiosyncratic price variance leads to lower transaction prices. For properties with a higher expected idiosyncratic price variance, the optimal bid, and consequently, the transaction price will be lower. All else being equal, a risk-averse buyer will choose to bid a lower amount for a property that has a more uncertain resale value.[26] Therefore, the model predicts that these properties should transact at a lower price.

$$\frac{\partial B^*}{\partial \sigma_p^2} = -(1-\alpha)\frac{1}{2}\beta^2 < 0 \quad (2.32)$$

P2. Higher idiosyncratic price variance leads to higher rental yields. Using equation (2.31) I write the ratio of the expected rental income in period 2 to the transaction price in period 1 as a function of the price idiosyncratic variance. Then

26. Please note that even if the buyer does sell the house in the future, the idiosyncratic component might still impact their optimal bid through the use of the house as a collateral.

taking the derivative with respect to the idiosyncratic price variance I get the following equation:

$$\frac{\partial \frac{E_1(R_2)}{B^*}}{\partial \sigma_P^2} = \frac{(1-\alpha)\frac{1}{2}\beta^2 * E_1(R_2)}{(1-\alpha)^2\left[\beta(ln(\mu_R) - \frac{1}{2}\sigma_R^2) + \beta^2(ln(\mu_P) - \frac{1}{2}\sigma_P^2) - \underline{PV_S}(h)\right]^2} > 0 \tag{2.33}$$

from which it becomes evident that the ratio of rents to prices, known as rental yield, increases with the idiosyncratic price variance. In other words, an investor will only be willing to offer a lower value for a given rental cash flow if they anticipate higher price uncertainty, which consequently mechanically increases the rental yield.

Nevertheless, if price uncertainty arises as a result of trading frictions in the housing market as shown in Sagi (2021), then we expect properties with higher price uncertainty to be traded in small and illiquid markets. This would mean that there are less potential renters for the property and, as such, the landlord would have less bargaining power. Other things constant, this would lead to a lower rental income, putting downward pressure on the rental yield. Which effect is stronger is not clear ex-ante and is, therefore, an empirical question.

P3. Higher idiosyncratic price variance does not result in excess capital gains but does lead to higher total returns. Due to the randomness of the resale price in the third period, this model does not make a prediction about the relation between capital gains and the idiosyncratic price variance. Nevertheless, the theoretical and empirical evidence on idiosyncratic price risk in housing markets shows that this risk primarily materializes at the point of sale and resale (Giacoletti, 2021; Sagi, 2021). Consequently, it arises primarily due to trading frictions in the housing market. In other words, idiosyncratic price variance is not driven by changes in the fundamental characteristics of the house and, thus, should not, on average, impact capital gains.[27] In conclusion, if properties with higher idiosyncratic price variance are expected to yield higher rental yields but no additional capital gains, then these properties should offer higher total returns.

Note that if a buyer owns multiple houses, they might be able to diversify away idiosyncratic price deviations. If this is the case, then in a standard asset-pricing model with complete markets, the idiosyncratic variance should not influence the market's stochastic discount factor. In Appendix 2.B, I demonstrate how the assumption of incomplete markets can lead to a market stochastic discount factor that also incorporates idiosyncratic price variance. This provides a theoretical

27. I provide a more detailed and extensive summary of this result in Appendix 2.A.

framework for idiosyncratic risk being priced in housing markets.

In this section, I have provided a stylised theoretical framework that predicts the empirical results about transactions prices and returns I showed in previous sections. In the next section, I will empirically test the assumptions of this model.

2.6 Market size, liquidity and value uncertainty

Drawing inspiration from theoretical frameworks that establish a relationship between market size and price dispersion in OTC markets (Gavazza, 2011), in this section, I empirically examine the connection between price uncertainty, market size, and market liquidity at the transaction property level. Given that houses are extremely heterogeneous goods and, consequently, exposed to highly diverse markets, it is crucial to investigate the relationship between price uncertainty and market size or liquidity at the transaction property level. Aggregation at higher levels might potentially obscure significant variations in the data.

2.6.1 Value uncertainty and market size

To measure market size at the property level, I rely on the literature on atypical properties (e.g. Haurin, 1988; Bourassa et al., 2009), and build an atypicality index for each transaction i based on the distance between the properties' characteristics and the average property in the neighborhood:

$$ATYP_i = \sum_n |exp(\hat{\beta}_n X_n) - exp(\hat{\beta}_n \overline{X}_n)|,$$

where $\hat{\beta}_n$ represent the shadow price of characteristic n estimated in a log-linear hedonic regression using all the transactions for the respective city. $\overline{X}_n$ is the average of characteristic n for all the transactions in the respective neighborhood. The $ATYP_i$ then measures the relative distance of the properties' characteristics to the mean, or typical, property in the neighborhood weighted by the shadow price of each characteristic. The higher the value of $ATYP_i$ the more atypical a property is with respect to the other properties in the neighborhood. As such, the atypicality index is a direct measure of the sellers' market size of the property. Through general equilibrium effects, we expect the demand for these type of properties to also be relatively low, altogether making the markets for atypical properties relatively small. In Figure 2.7, I plot a scattered bin plot of predicted dispersion on the atypicality index. For all cities in the sample there is a clear positive relation: properties with higher levels of idiosyncratic risk are also more atypical. In other words, properties transacted in smaller markets display larger levels of value uncertainty.

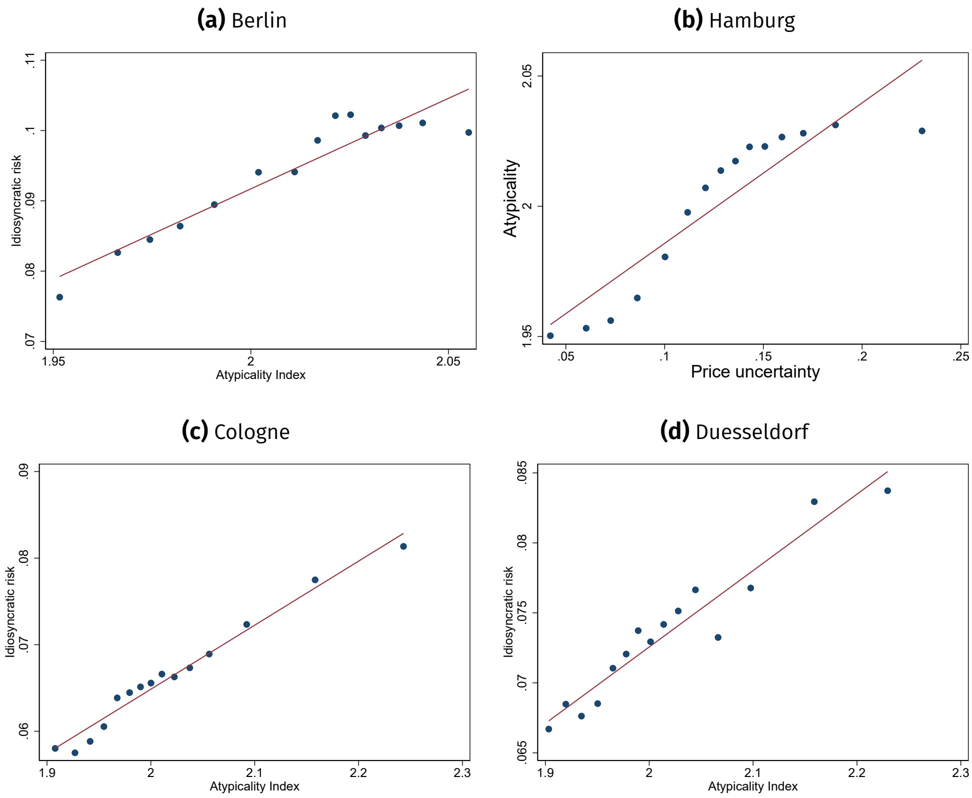

Figure 2.7. Value uncertainty and atypicality of the property

Note: The figure dispalys binscatters of predicted price dispersion on atypicality index at the transaction property level for all cities in the sample. In all binscatters the underlying regressions include year-quarter and neighborhood fixed-effects as well as controls for property characteristics.

The statistical significance of this relation is confirmed by the regression results in the tables in Appendix 2.G, which show that the relation between idiosyncratic risk and the atypicality index is positive and highly significant also when neighborhood and time fixed effects.

2.6.2 Value uncertainty and asset liquidity

Using the data set with matched transactions and advertisements I build two measures of asset liquidity at the transaction property level. Firstly, I created a measure of time on the market, defined as the number of weeks between the day the ad was posted and the day it was taken offline:

$$TOM_{it} = \frac{Number\ \ of\ \ days\ \ advertised}{7}$$

Secondly, I constructed a measure of the spread between the asking price and the transaction price as:

$$Spread_{it} = 100 \cdot \frac{(Sales\ price_{it} - Asking\ price_{it})}{Asking\ price_{it}}$$

To gain insight into the relation between value uncertainty and the expected duration a property stays on the market, it is essential to consider whether the listed property ultimately sells or not. In the literature on housing markets, hazard models have been employed to analyze the expected time a property spends on the market (Haurin, 1988; Han and Strange, 2015). Following the literature, I assume the following hazard function for time on the market:

$$h(tom) = h_0(tom) * exp[\gamma\hat{\sigma} + B_X X + \eta_{tq} + \kappa_n], \tag{2.34}$$

where $h_0(tom)$ is the baseline hazard rate and its specific shape will depend on the assumption about the distribution of the error term. The hazard rate $h(tom)$ then denotes the probability of a property being sold at time t, conditional on the seller listing the property to that point in time, and subject to the predicted dispersion, $\hat{\sigma}$, the property characteristics, X and the year-quarter, η_{tq}, and neighborhood, κ_n fixed effects. I estimated the hazard rate using various error term distributions and presented the results in Table 2.4. The first row of the table displays the effect of predicted dispersion on the hazard rate of time on the market, given by its hazard ratio. Across all specifications, it becomes evident that increased value uncertainty, as quantified by predicted price dispersion, is associated with higher expected time on the market. A one unit increase in value uncertainty is associated with more than doubling the probability that the property does not get sold.

Table 2.4. Expected time on the market and value uncertainty, Hamburg (2012-2022)

	Exponential	Weibull	Cox
Price uncertainty	2.58**	2.61***	2.66***
	(0.994)	(0.905)	(0.917)
Year-quarter FEs	Yes	Yes	Yes
Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
N	24497	24497	24497

Notes: The Table reports the results of three different duration models of time on the market. The first row displays the estimated hazard ratio of predicted dispersion. Standard errors are shown in parenthesis. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Having established that properties with greater predicted dispersion tend to, on average, spend a longer time on the market, the subsequent analysis narrows

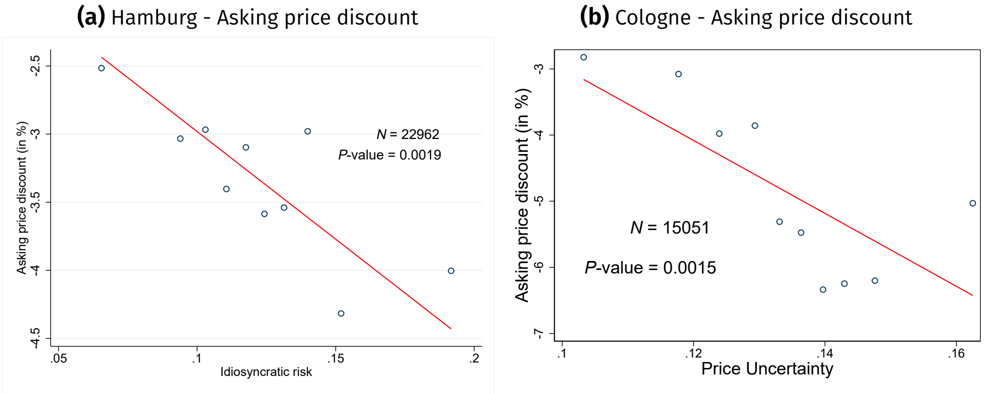

Figure 2.8. Predicted dispersion and asset level liquidity, Cologne (2012-2022)

Note: These figures display a binned scatter plot, based on a regression of spread on predicted dispersion, property characteristics and year-quarter and neighborhood fixed effects. The data shown is for the city of Cologne and Hamburg for the period between 2012 and 2022.

down to the subset of properties that have been successfully sold. In this context, I examine whether the transaction prices for these properties significantly differ from their initial asking prices. I regress the spread between the asking price and the transaction price on predicted price dispersion while controlling for property characteristics, neighborhood factors, and year-quarter fixed effects. The outcomes of this analysis are illustrated in Figure 2.8, and the visual representation makes it evident that properties characterized by higher value uncertainty generally sell at prices considerably lower than their initial asking prices. This finding aligns with Sagi (2021), who demonstrates that buyer-seller heterogeneity in private values plays a central role in explaining the idiosyncratic price dispersion.

Additionally, the trade-off between time on the market and asking price discount becomes greater with value uncertainty. It is a well-known trade-off that, to sell a house quickly, a seller has to accept a cut to the original asking price. I tested the effect of value uncertainty on this trade-off by running a regression of asking price discount on time on the market at the transaction level, where I also included an interaction term between time on the market and predicted dispersion. The results can be found in Table 2.5. The sign of the interaction coefficient is negative, meaning that for a given level of time on the market, a seller will need to accept a larger cut to the asking price when selling a property with more price uncertainty.

Table 2.5. Trade-off TOM and price discount, Cologne (2012-2022)

	Price Discount	Price Discount	Price Discount
TOM	-0.03***	0.04	0.04
	(0.007)	(0.026)	(0.025)
TOM × Idiosyncratic risk		-0.64**	-0.63***
		(0.198)	(0.181)
Idiosyncratic risk		-96.90***	-87.49***
		(15.957)	(14.083)
Year FEs	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	No	No	Yes
N	12830	12800	12800
R^2	0.02	0.05	0.06

Notes: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Singletons were dropped. $*$: $p < 0.1$; $**$: $p < 0.05$; $***$: $p < 0.01$.

Table 2.6. Trade-off TOM and price discount, Hamburg (2012-2022)

	Price Discount	Price Discount	Price Discount
TOM	0.01	0.08***	0.06***
	(0.009)	(0.019)	(0.019)
TOM × Idiosyncratic risk		-0.56***	-0.54***
		(0.155)	(0.160)
Idiosyncratic risk		-35.95***	-20.39***
		(5.290)	(4.830)
Year FEs	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	No	No	Yes
N	22861	22513	22513
R^2	0.02	0.03	0.04

Notes: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Singletons were dropped. $*$: $p < 0.1$; $**$: $p < 0.05$; $***$: $p < 0.01$.

2.7 Conclusion

Despite the extensive literature on the microstructure of housing markets, which has emphasized the significance of housing liquidity for patterns in housing prices, relatively little attention has been given to the interplay between liquidity in the rental and sales markets and its impact on transaction prices and returns. I begin by constructing a bargaining model involving a risk-averse investor who encounters uncertainty regarding future rental income and the property's value. The model predicts that properties with higher value uncertainty will be traded at lower prices and yield higher returns. To test the model's predictions, I utilize a novel transaction-level dataset encompassing all real estate transactions in major German cities over the past four decades. In each of the four cities in my sample, I find robust evidence that supports all three predictions of the model. In the context of the German housing markets, higher returns on properties with greater value uncertainty are plausible, given the larger size and liquidity of rental markets compared to sales markets.

While Germany has grappled with persistently low homeownership rates for decades, this paper sheds light on how the substantial size and liquidity of the rental market may impede policies aimed at increasing homeownership rates, as they provide higher returns for housing investments, making buy-to-let investments highly attractive.

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Appendix 2.A Idiosyncratic Price Dispersion in Housing Markets

A broad literature, which started with Case and Shiller (1988), has argued that the idiosyncratic component of prices is the largest determinant of capital gains for individual houses. Idiosyncratic house price risk is defined as the property-level capital gains not explained by local market fluctuations and common house or transaction characteristics. It can thus be estimated as the standard deviation of the residuals of a regression of house price appreciation on a set of controls:

$$\Delta p_{t+1}^{h} \quad = \Delta v_{t+1} + \quad BX^{h} + \quad \sigma_{l,residual}\ \rho_{t+1}^{h} \tag{2.A.1}$$

where $\Delta v_{l,t}$ represents the average growth of local house prices, X^h is a vector of property and transaction-specific characteristics that might impact the price and ε_t^h can be interpreted as a transaction-specific shock. Using very rich transaction-level data, recent work has demonstrated empirically that most of the variation in house prices is indeed idiosyncratic (Giacoletti, 2021; Sagi, 2021). In addition to finding a large amount of idiosyncratic volatility in house prices, these papers also show that the idiosyncratic component of volatility almost does not scale with the holding period. Instead, idiosyncratic volatility seems to stem mostly from the sale and re-sale of the property. This suggests that transaction frictions might explain most of the idiosyncratic risk in housing.

Sagi (2021) builds and calibrates a heterogeneous agents search model of the housing market, in which idiosyncratic volatility in house prices arises from limited trading opportunities and heterogeneity in valuations. In the model dispersion in the relative valuations of randomly matched counterparties and limited trading opportunities leads to uncertainty about the matching process and, therefore, to transaction risk. Illiquidity can thus amplify the house price risk. Sagi shows that one can write the log total return on a property for a specific period as the sum of a market-wide price shock μ_m, a shock to the value of the housing services η_{inc} and a transaction-specific shock ρ_{trans}:

$$\Delta r_{t+1}^{h} \quad = \sigma_m \mu_{m,t+1} + \sigma_{inc}\eta_{inc,t+1} + \sigma_{trans}\rho_{trans,t+1}^{h}, \tag{2.A.2}$$

where the housing services shock component can be decomposed into a market and an idiosyncratic component: $\sigma_{inc}\eta_{inc} = \sigma_{inc,m}\eta_{inc,m} + \sigma_{inc,idio}\eta_{inc,idio}$. The idiosyncratic component of the housing services shock together with the transaction shock build the property-level risk. In particular, the transaction shock maps one-to-one to the residual shock in equation 2.A.2. Sagi is also able to show empirically that the majority of property-level risk arises from the transaction risk and not from the idiosyncratic housing services shock component. As such, I will focus on this transaction shock as a source of risk premium in the theoretical analysis that follows.

Appendix 2.B Idiosyncratic risk in asset pricing

Sagi (2021) constructs a search model of the housing market, demonstrating that heterogeneity in the private valuations of sellers and buyers, coupled with market illiquidity, play a crucial role in explaining the deviations of individual real estate prices from their expected market values. When these deviations persistently occur for specific properties, meaning a property consistently transacts at a price significantly different from its expected market value, it becomes a source of risk for potential buyers. Consequently, buyers may consider this source of risk when determining the value they are willing to pay for a specific house. In other words, this idiosyncratic risk might be priced into housing markets.

However, in most asset-pricing theories, idiosyncratic risk is not priced in equilibrium, as it can be diversified away (Cochrane, 2009). Consequently, existing pricing models of the housing market often rely on this framework, concentrating solely on common risk factors (Piazzesi, Schneider, and Tuzel, 2007; Case, Cotter, and Gabriel, 2011). However, in an incomplete markets setting, households may not be able to fully diversifying their portfolios, thereby exposing them to idiosyncratic risks.

Inspired by the vast empirical evidence that households' consumption reacts to house price shocks (Attanasio, Leicester, and Wakefield, 2011; Mian, Rao, and Sufi, 2013; Stroebel and Vavra, 2019), I will setup a model in which idiosyncratic consumption depends on house price volatility. Based on household-level data, several papers have been able to isolate confounding factors, such as income expectations, to show that unexpected house price shocks causally lead to changes in consumption (e.g. Campbell and Cocco, 2007). More recently, Berger et al. (2018) show that large consumption responses to house price movements are fully in line with workhorse models of consumption with incomplete markets.

I build on the seminal work by Constantinides and Duffie (1996) to construct a housing asset-pricing model in which idiosyncratic price risk is a priced state variable, as idiosyncratic housing price volatility affects the average household's marginal utility through consumption. Since households cannot completely insulate their consumption from persistent shocks to their income (Blundell, Pistaferri, and Preston, 2008), the volatility of households' consumption growth distribution inherits the same factor structure as the volatility in property-level prices. In other words, persistent, idiosyncratic price shocks that hit houses are an important source of undiversifiable risk to households. Housing price risk thus enters the pricing kernel of households and, as a result, is a priced state variable.

This approach is very similar to the work from Herskovic et al. (2016). The authors build a heterogenous agent incomplete markets model, in which the idiosyncratic component of households' consumption follows the same structure as the common idiosyncratic volatility of firms' dividends. Since households cannot diversify away the idiosyncratic component of consumption, the firms' idiosyncratic volatility is priced in equilibrium. In contrast to stocks, idiosyncratic volatility in real estate arises mostly from shocks to house prices at the point of sale and re-sale. As such, it makes more sense to think of house price shocks as being the source of undiversifiable risk to households, rather than shocks to value of housing dividends (rents).

The theoretical framework presented here has two main caveats. Firstly, it considers only one risky asset, namely housing, thus ignoring any common risk sources that might arise from the covariance structure of returns to housing and other assets. Since this paper focuses on idiosyncratic risk, I abstract from several sources of common risk. Secondly, the model views housing as an investment good and does not consider its nature as a consumption good. However, as I demonstrate in more detail, this abstraction does not affect the main results of the model.

2.B.1 A Consumption Asset-Pricing Model with Idiosyncratic Risk

2.B.1.1 Setup

Households can invest both in a riskless asset with return r^f and in housing with return $R^h_{t+1} = \frac{P^h_{t+1}+D^h_{t+1}}{P^h_t}$, where P_t is the price and D_t the value of the housing services provided by the house at time t.

Following Berk, Green, and Naik (1999), I parameterize directly the pricing kernel without explicitly modelling the consumer's problem. The individual log stochastic discount factor is then:

$$m^i_{t+1} \;=\; log\beta - \gamma b^i \left[\sigma_{p,t+1} \upsilon_{idio,t+1} + \sigma_{idio,t+1} \rho^i_{t+1} - \frac{1}{2}\sigma^2_{idio,t+1}\right] \tag{2.B.1}$$

This equation can be motivated by assuming a fictitious consumer side problem with heterogeneous agents with power utility and a relative risk aversion coefficient, γ. The heterogeneity among home buyers comes from the fact that they will have different consumption sensitivities to house price shocks, given by the parameter b^i. This is motivated by the empirical evidence on the heterogeneity of consumption responses to house price shocks, for ex. older households respond more than younger households (Campbell and Cocco, 2007). Under this setup we can write the log individual sdf as:

$$m^i_{t+1} \;=\; log\beta - \gamma[b^i \Delta c^i_{t+1}]. \tag{2.B.2}$$

Following Constantinides and Duffie (1996) I will write log individual consumption c^i both as function of aggregate log consumption c^A as well as of the individual log share of aggregate consumption s^i:

$$\Delta c^i_{t+1} \;=\; b^i(\Delta c^A_{t+1} + \Delta s^i_{t+1}), \tag{2.B.3}$$

By linking aggregate consumption and the individual shares to house price shocks in reduced form as:

$$\Delta c^A_{t+1} = \sigma_{p,t+1} \upsilon_{t+1} \tag{2.B.4}$$

$$\Delta s^i_{t+1} = \sigma_{idio,t+1} \rho^i_{t+1} - \frac{1}{2} \sigma^2_{idio,t+1} \tag{2.B.5}$$

Equation 2.B.1 follows from the above equations. Note that while aggregate consumption growth is homoskedastic, individual consumption growth is not:

$$E_i[\Delta s^i_{t+1}] = -\frac{1}{2} \sigma^2_{idio,t+1} \tag{2.B.6}$$

$$V_i[\Delta s^i_{t+1}] = \sigma^2_{idio,t+1} \tag{2.B.7}$$

Assuming there are N housing investors in the economy, and that these investors have the same level of risk aversion we can write the average markets' sdf as the sum of the individual investors' sdf. Define $E_i = \frac{1}{N} \sum_{i=1}^{N}$ and note that since the idiosyncratic shock has mean zero, then, applying the law of large numbers, the term $\sigma_{idio} \rho^i$ converges to zero when we sum over the individual investors. Then we have:

$$E_i m^i_{t+1} = E_i(-\delta - \gamma \Delta c^i_{t+1}) \tag{2.B.8}$$

$$m^m_{t+1} = -\delta - \gamma(\sigma_{p,t+1} \upsilon_{t+1}) + \frac{1}{2} \sigma^2_{idio,t+1}, \tag{2.B.9}$$

where it becomes clear that the markets' sdf not only varies with aggregate housing price volatility, but also with the cross-sectional variance of housing prices, which is determined by the idiosyncratic housing price shocks. Assuming the pricing kernel is derived from the FOC of the consumer problem, I can write the riskless asset log return as:

$$\begin{aligned} 1 &= E_t[m^m_{t+1} r^f_{t+1}] \\ \iff \quad r^f_{t+1} &= \delta + \gamma(\sigma_{p,t+1} \upsilon_{t+1}) - \frac{1}{2} \sigma^2_{idio,t+1}, \end{aligned} \tag{2.B.10}$$

the log housing premium as:

$$E_t(r^h_{t+1}) - r^f_{t+1} = -r^f_{t+1} * cov(m^m_{t+1}, r^h_{t+1}), \tag{2.B.11}$$

where r^h_{t+1} is the total return to house h in period $t+1$. Multiplying and dividing by the variance of the markets' stochastic discount factor we can write the log housing premium in the standard beta representation form as:

$$E_t(r^h_{t+1}) - r^f_{t+1} \;=\; \beta_p \gamma \sigma^2_{p,t+1} + \beta_{idio} \gamma \sigma^2_{idio,t+1}. \tag{2.B.12}$$

This equation provides a linear relation between housing excess returns, systematic risk, σ_p, and idiosyncratic risk, σ_{idio}. In the next sections, I will first measure σ_{idio} and then test whether I can find a significant impact on housing returns.

Appendix 2.C Transaction-level data set

2.C.1 All sales

Table 2.C.1. Summary statistics for all apartment sales by city

	Berlin					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	190144	216	176.4	93.3	160.1	285
Size (m^2)	190144	76	29.9	55.1	70	92.7
Construction year	190144	1943	45.5	1905	1928	1991
Residuals, $u_{i,tq}$ (%)	190144	0	29.7	-17.6	0	19.2
Rental yield (%)	190144	3.4	1.8	2.2	3	4.1
	Hamburg					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	81840	296	256.6	128	222.5	376
Size (m^2)	81840	77	31	56	72	92.5
Construction year	81840	1972	38.4	1955	1974	2008
Residuals, $u_{i,tq}$ (%)	81840	0	24.8	-13.3	0	15.4
Rental yield (%)	81840	4.3	2	3	3.9	5.2
	Cologne					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	108103	159	124.4	80	122	195
Size (m^2)	108103	71	25.8	54	69	86
Construction year	108103	1972	25.6	1959	1972	1990
Residuals, $u_{i,tq}$ (%)	108103	0	25.1	-14.3	0	15.8
Rental yield (%)	108103	5.5	2.3	3.9	5.2	6.7
	Duesseldorf					
	N	Mean	SD	P25	Median	P75
Price (thousand €)	48893	184	175.7	81.3	126	214
Size (m^2)	48893	76	30.2	55	72	93
Construction year	48893	1965	27.5	1954	1965	1982
Residuals, $u_{i,tq}$ (%)	48893	0	26.3	-15.3	0	15.8
Rental yield (%)	48893	4.9	2.2	3.5	4.6	5.8

Note: Table reports summary statistics for all apartment sales for Berlin (1986-2022), Hamburg (2002-2022), Cologne (1989-2022) and Duesseldorf (1984-2022). Note that before 1992 the data for Berlin refers only to West-Berlin. Prices are in nominal terms.

2.C.2 Distribution of idiosyncratic price deviations

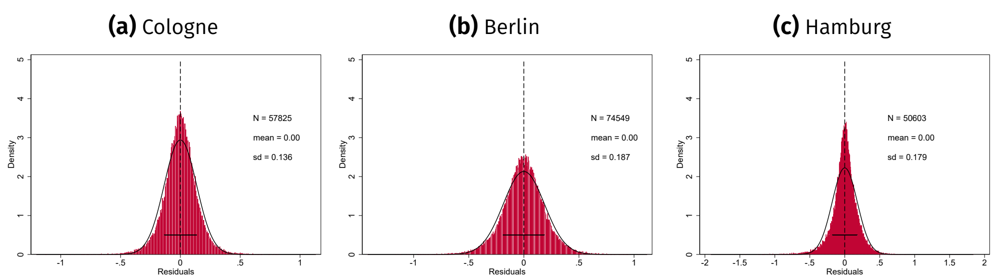

Figure 2.C.1. Distribution of idiosyncratic price deviations by city

Notes: This figure shows the distribution of residuals from equation (2.1) for Cologne (a), Berlin (b) and Hamburg (c).

2.C.3 Transaction data for Hamburg

In this section of the appendix, I provide a more detailed description of the method used to measure price dispersion at the transaction apartment level in the city of Hamburg. In the original dataset containing transactions for the city of Hamburg, information on apartment identification is missing in most cases. Consequently, it is impossible to identify repeated transactions of the same apartments over time. This limitation accounts for the low number of repeated sales available for the analysis of the effects of predicted dispersion on total returns and capital gains. Therefore, for Hamburg, I measure price dispersion without including apartment fixed effects. I employ the following specification to measure price deviations at the transaction apartment level:

$$ln(p_{i,tq}) = b_i + \eta_{tm} + \kappa_{n,tq} + f_c(x_i, ty) + u_{i,tq}, \tag{2.C.1}$$

where $u_{i,tq}$ is a mean-0 error term with variance σ^2 and b_i is a building fixed-effect. The other terms in the regression are the same as in the baseline specification (2.1). The most significant deviation from the baseline specification is that I am no longer controlling for apartment-specific features. Instead, I am accounting for features that remain constant within the building, such as the exact location.

Appendix 2.D Distribution of dispersion across space and time

By definition, a idiosyncratic shock should be uncorrelated with common shocks. More precisely, for each property i $E[e_{it}\mu_t] = 0$. Measuring common shocks directly is extremely complicated in housing markets, since this would require additional data on the supply and demand of housing markets. However, it is possible to measure common movements in the market. In other words, if the value of an apartment in the changes in response to a common shock, then we would expect the values of similar apartments nearby to also change. On the other hand, if the value changes in response to an idiosyncratic (property-level) shock, then we do not expect the value of similar apartments nearby to change. The idiosyncratic component of housing prices should be independently distributed across apartments. To test for this, I estimate spatial correlation in idiosyncratic shocks using Morans'I . A positive Morans'I indicates that apartments with positive residuals are surrounded by other apartments with positive residuals.[28] Figure 2.D.1 plots Morans'I for sales prices, property-level capital gains and idiosyncratic shocks of apartments sold in the same year in Cologne for the period between 1989 and 2022. Log sales prices and capital gains show a positive and significant spatial autocorrelation, which intuitively decreases with distance. If an apartment is sold for a high price, then probably the neighboring apartments will also sell for a high price. For idiosyncratic price shocks, I cannot reject the hypothesis that the correlation is 0, even when looking only at apartments sold within a three kilometer radius.

For the idiosyncratic shocks to matter, their variance needs to be persistent over time. If idiosyncratic shocks to housing prices would be transitory, then one could easily make the argument that a buyer should not care about such shocks. In other words, I want to test whether a large shock to a specific property todays, predicts a large shock in the future. Following the empirical evidence on idiosyncratic housing price shocks, here I am considering shocks that occur at the points of sale and re-sale. Specifically, I test for all pairs of transactions in the data set whether the variance of the shock at the point of sale predicts the variance of the shock at the point of re-sale:

$$u_{i2}^2 \; = \; \beta_1 u_{i1}^2 + \beta_2 hp_i + \kappa_{nt} + \lambda_m + \epsilon_{it}, \tag{2.D.1}$$

28. Morans'I test for spatial autocorrelation is estimated as:

$$I \; = \; \frac{N}{\sum_i \sum_j w_{i,j}} \frac{\sum_i \sum_j w_{i,j}(x_j - \bar{x})(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

with d_{ij} being the distance between apartment i and j in kilometers, k is the maximum radius in km and w_{ij} is one if the distance between i and j is smaller than k.

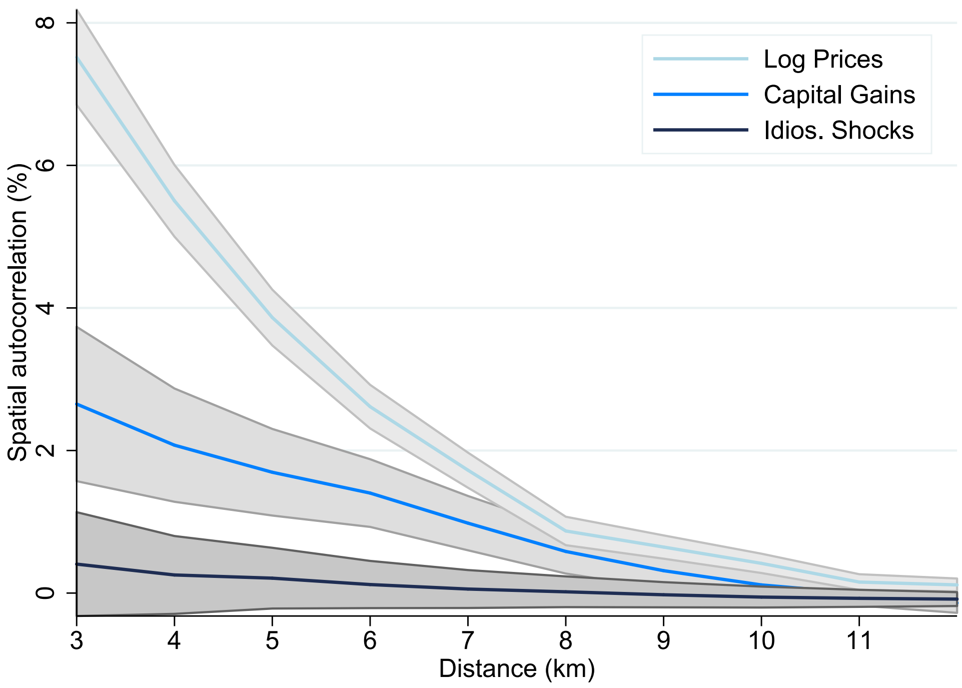

Figure 2.D.1. Spatial autocorrelation in housing market outcomes

Note: Morans'I is estimated for apartments sold in the same year and within the given km radius for the city of Cologne between 1989 and 2022. The Figure shows the simple average across years of Morans'I for each radius. 95% confidence interval bands are shown in the shaded areas.

where e_{i2} and e_{i1} are the idiosyncratic price shocks at the points of re-sale and sale respectively of property i. hp_i measures the holding period in months for property i, while δ_m are monthly fixed effects and κ_t are neighborhood fixed effects. The results can be found in Table 2.D.1, which shows that properties sold and re-sold on the same in the same month and neighborhood show considerable persistence in their idiosyncratic shocks. An increase in one standard deviation of the sales' shock predicts an increase in 0.66 standard deviations in the resale shock. One concern is that these results are being driven by the buyers, if a specific buyer is bad at pricing a house at the moment of sale, then probably as well at the moment of re-sale. This could potentially explain the high level of persistence in the variance. To address this concern, I show that the persistence in variance is also strongly positive and statistically significant when testing the relation between first and third sale. The results can be found in Table 2.D.2. Additionally, the cross-sectional correlation at the point of sale and re-sale of idiosyncratic shocks is 0.66, which is higher that than most risk factors used in the stock pricing literature (Bali, Engle, and Murray, 2016).

Table 2.D.1. Persistence in the variance of idiosyncratic shocks

	u_{i2}^2	u_{i2}^2
u_{i1}^2	0.6485***	0.6479***
	(0.0166)	(0.0167)
Holding period	Yes	Yes
Month-sale FEs	Yes	Yes
Neighborhood FEs	No	Yes
N	34060	34060
R^2	0.43	0.43

Notes: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Coefficients are standardized. Singletons were dropped. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

In Table 2.D.2, I test whether the variance of the idiosyncratic shock at the point of the first sales predicts the variance of the shock at the third sale.

Table 2.D.2. Persistence in the variance of idiosyncratic shocks

	u_{i3}^2	u_{i3}^2
u_{i1}^2	0.3161***	0.3144***
	(0.0257)	(0.0260)
Holding period	Yes	Yes
Month-sale FEs	Yes	Yes
Neighborhood FEs	No	Yes
N	7244	7244
R^2	0.13	0.14

Notes: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Coefficients are standardized. Singletons were dropped. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

In Figure 2.D.2, I plot the Pearson cross-sectional correlation in idiosyncratic shock variance by holding period. The average cross-section correlation is 0.66 indicating that the variance of the shocks is highly persistent over time. In contrast, the cross-sectional correlation of market betas is at most 0.60 and decreases with the time distance. In the case of idiosyncratic housing price shocks, the cross-section correlation increases with the holding period, indicating that the variance of the shocks is more persistent for pairs of sales more distant in time.

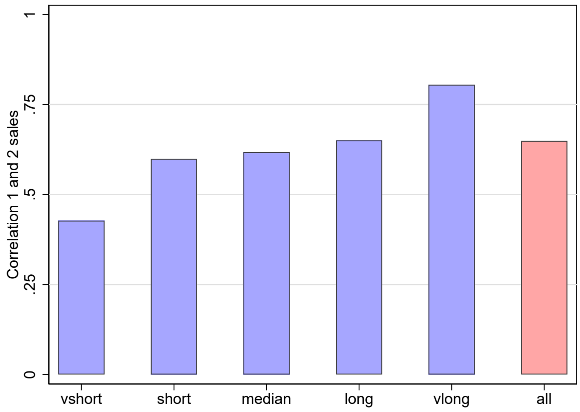

Figure 2.D.2. Pearson cross-section correlation in the predicted price dispersion

Note: Figure shows Pearson cross-section correlation of standardized residuals from sale 1 and 2 for different holding periods.

Appendix 2.E Hedonic price and rental yield indices

In this section of the appendix, I describe the hedonic methods employed to construct the two components of the total housing return portfolio quarterly time-series. Both for the price index as well as the rental yield index, I employ a rolling-window time-dummy hedonic index. The rolling-window component assures that the coefficients can change over time, i.e. the effect of age on the price can change over time. I set the rolling window at 20 quarters. More specifically, I employ the following log-linear specification:

$$ln(y_{i,tq}) = \beta^0 + \sum_{\tau}^{20} \gamma_\tau D_\tau + \sum_{k=1}^{K} (\beta^k x_i^k) + \epsilon_{i,tq}, \tag{2.E.1}$$

where the log dependent variable (transaction price, rental yield) for property i in quarter tq is regressed on a time-dummy D_τ and a set of property characteristics x_i, which consist of apartment size, age and neighborhood.

Appendix 2.F Idiosyncratic price uncertainty, sales prices and rents

2.F.1 Regression results for the main sample

In this section of the appendix, I provide the regression output tables for the analyses that form the basis of Figure 2.2 in the paper. Figure 2.2 illustrates the relationship between predicted price dispersion and both sales prices and rents for each city in the sample. The regression output is displayed in the following tables for each city separately. Please note that the specification that underlies the binned scatter in the paper is always in columns 2 and 4 for sales price and net rent respectively. From the tables, it is visible that the coefficient of predicted price dispersion on sales prices is much larger than the one on net rents. Additionally, the coefficient on net rents is mostly statistically insignificant, indicating that rents decrease very only slightly with idiosyncratic price uncertainty.

Table 2.F.1. Predicted price dispersion, sales prices and rent (Berlin)

	Sales Price	Sales Price	Net Rent	Net Rent
Predicted dispersion, $\hat{\sigma}_{it}$	-13.88***	-0.65***	-22.03***	0.15
	(1.341)	(0.129)	(2.708)	(0.183)
Year-quarter FEs	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes
N	67194	67194	67194	67194
R^2	-3.89	0.70	-8.08	0.93

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.F.2. Predicted price dispersion, sales prices and rent (Hamburg)

	Sales Price	Sales Price	Net Rent	Net Rent
Predicted dispersion, $\hat{\sigma}_{it}$	-9.72***	-1.51***	-12.13***	0.31
	(0.976)	(0.209)	(1.338)	(0.227)
Year-quarter FEs	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes
N	52647	52647	52647	52647
R^2	-2.06	0.70	-2.61	0.92

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.F.3. Predicted price dispersion, sales prices and rent (Cologne)

	Sales Price	Sales Price	Net Rent	Net Rent
Predicted dispersion, $\hat{\sigma}_{it}$	-34.36***	-1.45***	-42.12***	0.80*
	(3.671)	(0.443)	(4.456)	(0.424)
Year-quarter FEs	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes
N	50029	50029	50029	50029
R^2	-4.30	0.82	-6.84	0.96

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.F.4. Predicted price dispersion, sales prices and rent (Duesseldorf)

	Sales Price	Sales Price	Net Rent	Net Rent
Predicted dispersion, $\hat{\sigma}_{it}$	-17.71***	-2.47***	-18.58***	-0.80***
	(1.326)	(0.314)	(1.379)	(0.189)
Year-quarter FEs	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes
N	25971	25971	25971	25971
R^2	-3.78	0.68	-4.63	0.86

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $*$: $p < 0.1$; $**$: $p < 0.05$; $***$: $p < 0.01$.

2.F.2 Regression results for the sub-sample

In this subsection, I examine the relationship between predicted price dispersion and sales prices and rents, utilizing a subsample of observations for which data on both rent and sales price are available. The results mirror the patterns observed in the analysis of the full sample, indicating that prices tend to decrease more than rents in response to idiosyncratic price uncertainty. However, it is noteworthy that in some cities, the coefficients loose statistical significance. This was expected given the considerable reduction in the sample size.

Table 2.F.5. Idiosyncratic price uncertainty, sales prices and rent (Berlin-subsample)

	Sales Price	Sales Price	Net Rent	Net Rent
Predicted dispersion, $\hat{\sigma}_{it}$	-1.93***	-1.31***	-2.48***	-0.60*
	(0.454)	(0.326)	(0.516)	(0.317)
Year-quarter FEs	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes
N	13466	13466	13466	13466
R^2	0.04	0.72	-0.07	0.62

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 2.F.6. Idiosyncratic price uncertainty, sales prices and rent (Hamburg-subsample)

	Sales Price	Sales Price	Net Rent	Net Rent
Predicted dispersion, $\hat{\sigma}_{it}$	-1.89***	-0.86***	-1.88***	-0.42
	(0.378)	(0.247)	(0.494)	(0.322)
Year-quarter FEs	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes
N	8651	8651	8651	8651
R^2	0.03	0.66	-0.03	0.56

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 2.F.7. Idiosyncratic price uncertainty, sales prices and rent (Duesseldorf-subsample)

	Sales Price	Sales Price	Net Rent	Net Rent
Idiosyncratic uncertainty, $\hat{\sigma}_{it}$	-5.85***	-0.50	-6.67***	0.08
	(0.766)	(0.408)	(0.868)	(0.169)
Year FEs	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes
N	1321	1321	1321	1321
R^2	0.40	0.86	0.25	0.96

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $*: p < 0.1$; $**: p < 0.05$; $***: p < 0.01$.

Appendix 2.G Idiosyncratic risk and Atypicality index

Table 2.G.1. Idiosyncratic risk & atypicality of properties, Berlin

	OLS	OLS
Atypicality	0.26***	0.24***
	(0.014)	(0.011)
Year-quarter FEs	No	Yes
Year × Neighborhood FEs	No	Yes
N	74170	74170
R^2	0.05	0.45

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Singletons were dropped. The explanatory variable of interest is the dissimilarity index. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.G.2. Idiosyncratic risk & atypicality of properties, Duesseldorf

	OLS	OLS
Atypicality	0.05***	0.05***
	(0.004)	(0.003)
Year-quarter FEs	No	Yes
Year × Neighborhood FEs	No	Yes
N	32735	32735
R^2	0.03	0.29

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Singletons were dropped. The explanatory variable of interest is the dissimilarity index. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.G.3. Idiosyncratic risk & atypicality of properties, Hamburg

	OLS	OLS
Atypicality	0.35***	0.33***
	(0.015)	(0.015)
Year-quarter FEs	No	Yes
Year × Neighborhood FEs	No	Yes
N	53825	53825
R^2	0.17	0.45

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Singletons were dropped. The explanatory variable of interest is the dissimilarity index. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.G.4. Idiosyncratic risk & atypicality of properties, Cologne

	OLS	OLS
Atypicality	0.07^{***}	0.07^{***}
	(0.003)	(0.002)
Year-quarter FEs	No	Yes
Year × Neighborhood FEs	No	Yes
N	62232	62232
R^2	0.06	0.15

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Singletons were dropped. The explanatory variable of interest is the dissimilarity index. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Appendix 2.H Price uncertainty and dispersion of prices

In this section of the appendix, I show how price uncertainty also affects the second moment of the distribution of transaction prices. Since I do not observe properties that have been sold every period, my analysis will explore the cross-sectional variation in prices of similar houses. My analysis will follow two steps. In the first step, I residualize the transaction prices using property characteristics and time and location fixed effects. In a second step, I split the transactions into 10 different bins depending on their level of price uncertainty. I then calculate the standard deviation of prices within those bins and plot them in Figure 2.H.1. From the Figure it becomes clear that properties with higher ex-ante price uncertainty also have a higher standard deviation of prices. This means that price uncertainty predicts lower prices and higher dispersion.

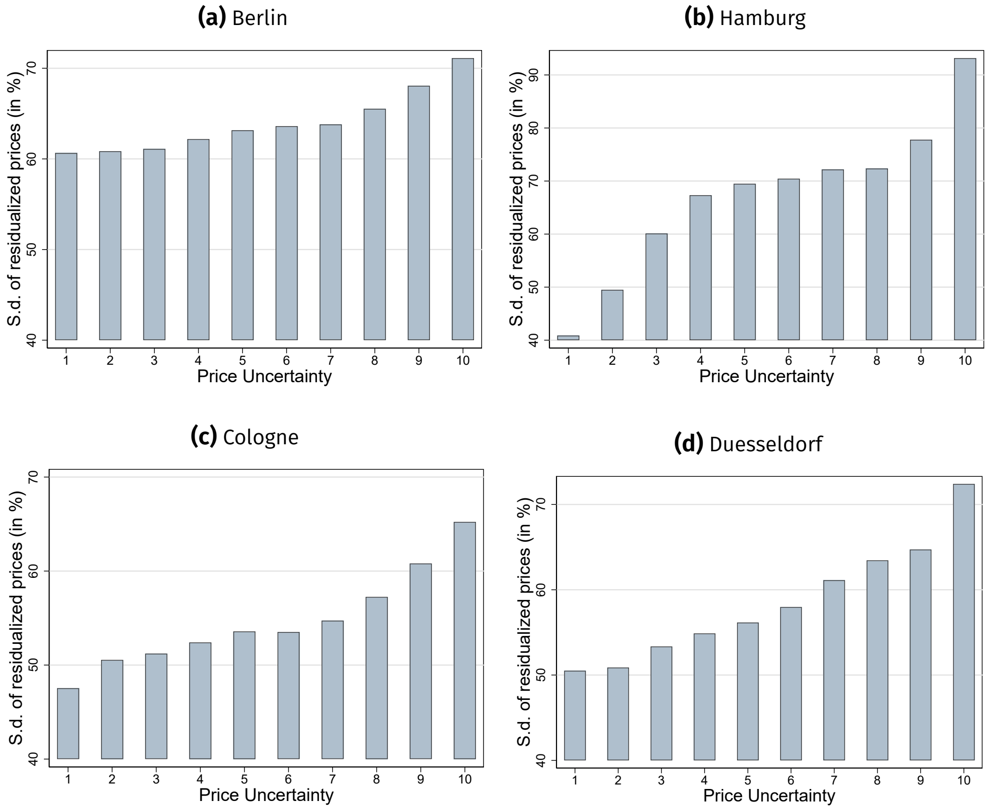

Figure 2.H.1. Price uncertainty and dispersion of prices

Note: The figure displays the standard deviation of residualized log transaction prices across the price uncertainty distribution for the different cities in the data set.

Appendix 2.I Predicted dispersion and returns to housing - regression output

2.I.1 Predicted dispersion and rental yields - robustness

To address any biases that might arise from the matching process between transaction prices and rental values, I replicate the exercise in the previous sectios using only the subsample of transactions for which I also observe the rent data at the point of transaction. The results can be found in Figure 2.I.1, which shows that the main results hold. Comparing transactions in the same neighborhood and year-quarter and controlling for size and property characteristics, the data shows that properties with higher predicted dispersion, on average, have significantly higher rental yields than the rest.

Table 2.I.1. Predicted dispersion and total returns, Berlin (1984-2022)

	Rental Yields	Capital Gains	Total Returns
Predicted dispersion, $\hat{\sigma}_{i,tq}$	2.56***	4.70	7.71**
	(0.445)	(2.806)	(3.061)
Year-quarter FEs	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
Holding period FEs	No	Yes	Yes
N	67194	33309	33309
R^2	0.12	0.35	0.32

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk) and are adjusted for the estimated regressors. Singletons were dropped. The explanatory variable of interest is predicted dispersion. The first column displays the results of 2SLS regressions as in (2.7). Columns 2 and 3 display the results of the two-step regression as in (2.13). $*: p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 2.I.2. Predicted dispersion and total returns, Hamburg (2001-2022)

	Rental Yields	Capital Gains	Total Returns
Predicted dispersion, $\hat{\sigma}_{i,tq}$	8.72***	-1.04	1.74
	(0.768)	(7.500)	(8.281)
Year-quarter FEs	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
Holding period FEs	No	Yes	Yes
N	49506	1741	1741
R^2	-0.06	0.27	0.28

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk) and are adjusted for the estimated regressors. Singletons were dropped. The explanatory variable of interest is predicted dispersion. The first column displays the results of 2SLS regressions as in (2.7). Columns 2 and 3 display the results of the two-step regression as in (2.13). $*: p < 0.1; ** : p < 0.05; *** : p < 0.01$.

2.I.2 Predicted dispersion and rental yields - multi-family housing

In this section of the appendix, I present the regression outputs that form the basis for the results regarding the relationship between predicted dispersion and rental yields in the multi-family housing market. The tables that follow are generated from regression equation (2.7) with the ratio of net rental income to transaction price of multi-family houses as the dependent variable. The data samples used are drawn from multi-family housing transactions in Berlin spanning the period from 1970 to 2022 and in Hamburg from 1991 to 2022. For this analysis, I include

Table 2.I.3. Predicted dispersion and total returns, Cologne (1989-2022)

	Rental Yields	Capital Gains	Total Returns
Predicted dispersion, $\hat{\sigma}_{i,tq}$	16.28***	7.61	16.77**
	(3.368)	(4.544)	(6.220)
Year-quarter FEs	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
Holding period FEs	No	Yes	Yes
N	49963	27069	27069
R^2	-0.17	0.31	0.28

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk) and are adjusted for the estimated regressors. Singletons were dropped. The explanatory variable of interest is predicted dispersion. The first column displays the results of 2SLS regressions as in (2.7). Columns 2 and 3 display the results of the two-step regression as in (2.13). $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.I.4. Predicted dispersion and total returns, Duesseldorf (1984-2022)

	Rental Yields	Capital Gains	Total Returns
Predicted dispersion, $\hat{\sigma}_{i,tq}$	6.59***	1.22	5.76**
	(0.730)	(1.605)	(2.049)
Year-quarter FEs	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
Holding period FEs	No	Yes	Yes
N	25238	13037	13037
R^2	0.15	0.27	0.25

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk) and are adjusted for the estimated regressors. Singletons were dropped. The explanatory variable of interest is predicted dispersion. The first column displays the results of 2SLS regressions as in (2.7). Columns 2 and 3 display the results of the two-step regression as in (2.13). $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

only those transactions for which both the rental income and the transaction price are observed.

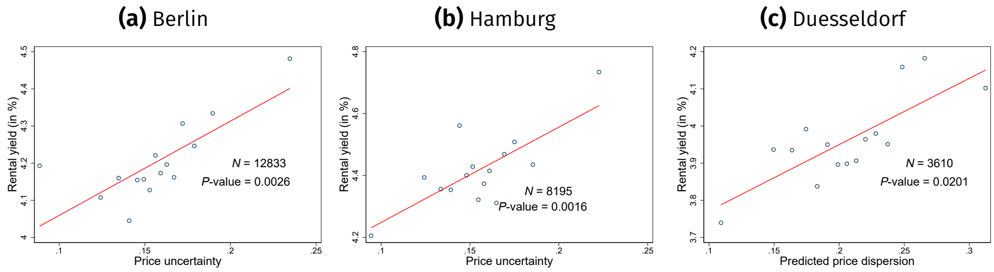

Figure 2.I.1. Rental yields and predicted dispersion using observed rent data

Note: The first and last columns display a binscatter of log sales price and rental yields on idiosyncratic risk respectively. The second columns displays a binscatter of capital gains on the sum idiosyncratic risk from sale and re-sale. In all binscatters the underlying regressions include year-quarter and neighborhood fixed-effects as well as controls for property characteristics.

Table 2.I.5. Predicted dispersion and rental yields for multi-family housing, Berlin (1970-2022)

	Rental Yield	Rental Yield	Rental Yield (wo mixed-use)
Predicted Dispersion, $\hat{\sigma}_{i,tq}$	2.38^{*}	5.03^{**}	4.17^{**}
	(1.306)	(1.031)	(1.139)
Year-quarter FEs	Yes	Yes	Yes
Year $\times$ Neighborhood FEs	Yes	Yes	Yes
Property characteristics	No	Yes	Yes
N	14332	14332	6841
R^2	0.00	-0.07	-0.02

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk) and are adjusted for the estimated regressors. Singletons were dropped. The explanatory variable of interest is predicted dispersion. All the columns display the results of 2SLS regressions as in (2.7) with ratio of net rental income to transaction price as the outcome variable The third column displays results only for the sample of multi-family housing that do not have any kind of commercial properties. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.I.6. Predicted dispersion and rental yields for multi-family housing, Hamburg (1991-2022)

	Rental Yield	Rental Yield	Rental Yield (wo mixed-use)
Predicted Dispersion, $\hat{\sigma}_{i,tq}$	7.93**	8.60**	6.76***
	(3.259)	(3.366)	(2.006)
Year-quarter FEs	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
N	7633	7633	5171
R^2	-0.00	-0.02	0.02

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk) and are adjusted for the estimated regressors. Singletons were dropped. The explanatory variable of interest is predicted dispersion. All the columns display the results of 2SLS regressions as in (2.7) with ratio of net rental income to transaction price as the outcome variable The third column displays results only for the sample of multi-family housing that do not have any kind of commercial properties. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Appendix 2.J Robustness Tests

2.J.1 All sales

In this section of the Appendix, I present the results for the analysis in which I utilize all property sales data to measure value uncertainty at the transaction property level, not just focusing on repeated property sales. The objective of this analysis is to ensure that the results are not influenced by specific characteristics of properties that are sold more frequently, which could distinguish them from the rest of the housing stock. The results for each city can be found in the tables below. These results corroborate the findings from the baseline analysis. Properties with higher value uncertainty are, on average, transacted at lower prices and yield higher rental returns. Once again, there is no statistically significant relationship between value uncertainty and the rental value of the property, affirming that the rental market is relatively liquid, and therefore, these properties are not rented out at a discount.

Table 2.J.1. Predicted price dispersion, sales prices and rent using all sales (Berlin 1984-2022)

	Sales Price	Sales Price	Net Rent	Net Rent	Rental Yield	Rental Yield
Predicted dispersion, $\hat{\sigma}_{it}$	-5.91***	-1.11***	-8.68***	-0.09	2.23**	4.72***
	(0.545)	(0.182)	(1.132)	(0.235)	(0.930)	(0.530)
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes	No	Yes
N	190144	190144	190144	190144	190144	190144
R^2	-1.70	0.63	-3.27	0.90	0.09	0.07

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables in columns 1 to 4 have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

Table 2.J.2. Predicted price dispersion, sales prices and rent using all sales (Hamburg 2001-2022)

	Sales Price	Sales Price	Net Rent	Net Rent	Rental Yield	Rental Yield
Predicted dispersion, $\hat{\sigma}_{it}$	-6.72***	-1.39***	-7.76***	0.85***	7.87***	9.25***
	(1.273)	(0.211)	(1.678)	(0.147)	(0.817)	(1.128)
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes	No	Yes
N	81840	81840	81840	81840	81840	81840
R^2	-1.78	0.69	-1.93	0.89	-0.06	-0.21

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables in columns 1 to 4 have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 2.J.3. Predicted price dispersion, sales prices and rent using all sales (Cologne 1989-2022)

	Sales Price	Sales Price	Net Rent	Net Rent	Rental Yield	Rental Yield
Predicted dispersion, $\hat{\sigma}_{it}$	-6.81***	-0.27	-7.33***	0.87**	7.70***	5.52***
	(1.169)	(0.303)	(1.056)	(0.292)	(2.012)	(0.552)
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes	No	Yes
N	108103	108103	108103	108103	108103	108103
R^2	-1.44	0.71	-1.79	0.91	-0.03	0.13

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables in columns 1 to 4 have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 2.J.4. Predicted price dispersion, sales prices and rent using all sales (Duesseldorf 1984-2022)

	Sales Price	Sales Price	Net Rent	Net Rent	Rental Yield	Rental Yield
Predicted dispersion, $\hat{\sigma}_{it}$	-7.54***	-0.53***	-8.02***	0.74***	9.72***	6.90***
	(1.087)	(0.164)	(1.163)	(0.111)	(1.592)	(0.914)
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year × Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Property characteristics	No	Yes	No	Yes	No	Yes
N	48893	48893	48893	48893	48893	48893
R^2	-2.34	0.73	-2.84	0.85	-0.28	0.06

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). The outcome variables in columns 1 to 4 have been standardized to have mean 0 and standard deviation of one. Singletons were dropped. The explanatory variable of interest is predicted price dispersion. The coefficients are estimated in the 2SLS regression framework of (2.7). $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

2.J.2 Different measures of predicted dispersion

This suggests that a significant proportion of the impact of my measure of idiosyncratic risk on sales prices can be attributed to variations in observable property traits. To tackle this issue, I devise an instrumental variable that approximates the idiosyncratic price risk without being directly dependent on the property characteristics. Following Jiang and Zhang (2022), I build an instrument based on the distance of the properties' i characteristics to the mean characteristics of the properties' sold in the same city and within the same period:

$$Z_{it}^{m} = (X_{it}^{m} - \bar{X}_{ct}^{m})^2, \ \forall m \in \{size, age, location\}. \tag{2.J.1}$$

This measure captures the degree of thinness in the local property market for property i, which in turn reflects the uncertainty surrounding its sales price. For instance, pricing an old and large apartment in a neighborhood predominantly composed of new and small apartments can be challenging. Additionally, I also build a measure based directly on the relative frequency of the combination of characteristics of an apartment. Every quarter I assign each transaction a specific bin depending on its size, location and age. The idea is to capture how frequently a specific combination of characteristics appears on the market at a given point in time:

$$Z_{it}^{m} = \frac{\#obs_{it}}{\#obs_t}, \ \forall m \in \{size, age, location\} \tag{2.J.2}$$

Building upon these concepts, I perform two-stage least squares (2SLS) regressions by utilizing the distances and the relative frequency Z_i as instruments to approximate the variance of the idiosyncratic price deviations:

$$\text{Stage 1:} \quad u_{it}^2 = \alpha + \beta_1 Z_{it}^{age} + \beta_2 Z_{it}^{size} + \beta_3 Z_{it}^{location} \tag{2.J.3}$$

$$+ B_X X_i + \kappa_{nt} + \mu_d + e_{it} \tag{2.J.4}$$

$$\text{Stage 2:} \quad ln(P_{it}) = \alpha + \gamma \hat{u}_{it} + B_X X_i + \kappa_{nt} + \mu_d + \epsilon_{it}. \tag{2.J.5}$$

The outcome of the 2SLS regressions for Berlin are presented in Table 2.J.5 and for Hamburg in Table 2.J.6. For the purpose of comparison, I have also included the results of my main baseline analysis in the first column. The coefficients remain negative and highly statistically significant, and it are of similar size to the coefficient of my baseline analysis. This indicates that these measures directly capture a significant portion of the variation in the sales price that is not explained by the property characteristics or the time-fixed effects, but rather by the degree of idiosyncratic sales price risk.

Table 2.J.5. Log sales prices and idiosyncratic risk (Berlin, 1989-2022)

	Benchmark	Distance	Frequency
Log idiosyncratic risk, $\hat{\sigma}_{it}$	-0.0444***	-0.0323***	-0.0484***
	(0.0144)	(0.0063)	(0.0081)
Year-month FEs	Yes	Yes	Yes
Quarter × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
N	69123	69123	69123
R^2	0.63	0.64	0.63

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Coefficients are estimated via two-stage least squares. Singletons were dropped. The explanatory variable of interest is idiosyncratic risk. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Table 2.J.6. Log sales prices and idiosyncratic risk (Hamburg, 2002-2022)

	Benchmark	Distance	Frequency
Log idiosyncratic risk, $\hat{\sigma}_{it}$	-0.0297***	-0.0407***	-0.0261***
	(0.0073)	(0.0043)	(0.0077)
Year-month FEs	Yes	Yes	Yes
Quarter × Neighborhood FEs	Yes	Yes	Yes
Property characteristics	Yes	Yes	Yes
N	53824	53824	53824
R^2	0.70	0.69	0.70

Note: Standard errors are clustered at the neighborhood-level (Stadtbezirk). Coefficients are estimated via two-stage least squares. Singletons were dropped. The explanatory variable of interest is idiosyncratic risk. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

2.J.3 Building renovations and predicted dispersion

In Figure 2.J.1, panel a, I plot the excess returns adjusted for the exposure to the market portfolio for all the six portfolios. Again, the portfolio containing the properties with the highest level of idiosyncratic risk overperforms all the othe portfolios. Panel b shows that the exposure to the market portfolio is almost flat across the idiosyncratic risk ditribution.

2.J.4 Length of holding periods and predicted dispersion

Following the same steps as before, I build different portfolios based on this new measure of the variance of shocks. I then compare the returns to these portfolios and find the same pattern as in the baseline analysis.

(a) alpha **(b)** market beta

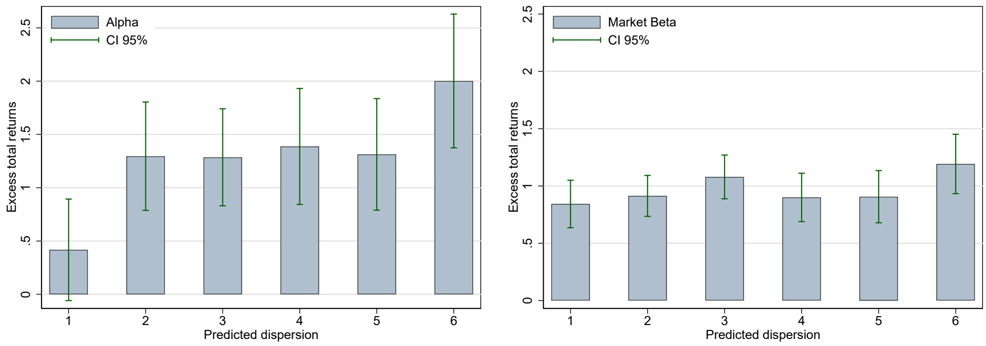

Figure 2.J.1. Excess returns with building-time fixed effects, Cologne 1989-2022

Note: The six equally-sized portfolios are built based on predicted variance of idiosyncratic shocks quantiles from equation 2.17. Standard errors are adjusted for time-series autocorrelation using Newey-West with 4 quarter lags.

(a) alpha **(b)** market beta

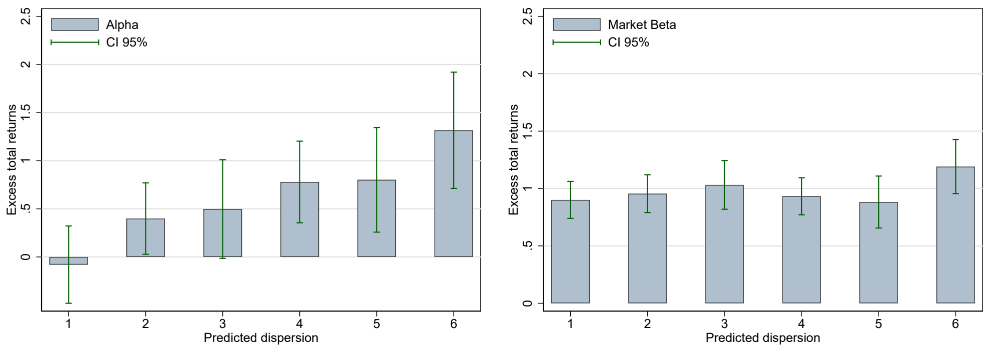

Figure 2.J.2. Excess returns controlling for holding periods, Cologne 1989-2022

Note: The six equally-sized portfolios are built based on predicted variance of idiosyncratic shocks quantiles from equation 2.18. Standard errors are adjusted for time-series autocorrelation using Newey-West with 6 quarter lags.

Appendix 2.K Rent data sources

2.K.1 Source

The rent data comes from the so-called 'Mietspiegel,' which are documents produced at the city level containing estimates for the average rent per square meter for apartments in the private market, depending on their size, building year, location and condition. The data is collected via a survey, and then the aggregate estimates are published every two years. The Mietspiegel provides benchmark rents that can be used by landlords to set their rents. If the rents deviate significantly from the benchmarks provided in the Mietspiegel, tenants have the option to file an official complaint. In such cases, landlords are obliged to adjust the rents to a level that aligns more closely with the Mietspiegel benchmarks. The publication of the Mietspiegel is typically the responsibility of the city. Until the 2000s, the data collection and estimates in the Mietspiegel were mostly produced by the city itself. Since then, most cities have started to hire specialized companies, which typically survey larger samples and produce rent estimates based on hedonic regressions. As a result, the quality of the estimates has substantially improved in the last 20 years (Steffen and Memis, 2021). The quality of the estimates provided by the Mietspiegel has been examined in several research papers. Specifically, researchers have sought to analyze the reliability of rental estimates derived from the Mietspiegel by comparing them to estimates based on alternative sources of rent data. In a study by Thomschke (2022), micro-level rents from the German census and online asking rents were utilized to generate rent estimates for the segments represented in the Mietspiegel for major German cities. The authors then compared their own estimates with those from the Mietspiegel and found minimal differences, thus affirming the validity of the estimates provided by the Mietspiegel. On the other hand, Rendtel, Sebastian, and Frink (2021) claims that the Berlin Mietspiegel underestimates the average value of rents by approximately 14% due to oversampling of large landlords. However, it is worth noting that this bias appears to be evenly distributed across all rent classes and, therefore, does not significantly impact the comparisons across rent classes, which are more relevant for the results I present.

Overall, the key point is that rental returns tend to increase with idiosyncratic risk. This relationship is clearly evident in cases where I have access to both rental and price data for the same property. Furthermore, it appears that this relationship holds true when using the Mietspiegel data as well, indicating its reproducibility.

2.K.2 Matching process

All the rent estimates provided in the Mietspiegel are net of utilities, meaning they do not include heating, water, electricity, and maintenance costs. The rent estimates are provided based on different criteria such as building years, size, location, and condition of the apartments. Additionally, only monthly rent per square meter estimates are provided. Regarding building years, the Mietspiegel typically distinguishes between apartments built before WWI, between WWI and WWII, and provides estimates for each post-WWII decade. In terms of size, the Mietspiegel typically categorizes apartments as less than 40 square meters, between 40 and 60 square meters, between 60 and 90 square meters, and more than 90 square meters. For location, the Mietspiegel usually differentiates between regions of varying quality within the city, commonly referred to as bad, middle, and good-quality regions. In most cases, the information about location quality is already available in the transaction data set. Lastly, the Mietspiegel also distinguishes between apartments with an own bathroom or central heating and those that have both of these amenities. As is expected, the rents are higher for those apartments, which have both of these amenities. This distinction is typically only done for apartments that were built before the 1970s, as the majority of apartments built after have both of these amenities.

Overall, the Mietspiegel provides a wide range of rent per square meter estimates based on the mentioned characteristics. By using the building year, size, and location quality, I am able to match the transaction data with the corresponding rent per square meter estimates. The only category that presents challenges in terms of matching is whether the apartment has its own bathroom or central heating. As previously stated, this issue primarily affects properties built before the 1970s.

In my primary analysis, I focus solely on rent estimates for apartments with both central heating and an own bathroom. However, it's important to acknowledge that this approach may introduce potential bias into the results by potentially overestimating the rental yields for properties with higher idiosyncratic risk.

To address this concern, I conduct a robustness analysis where I match transactions to the rent data based on the relative value of the transactions in that specific year, along with their corresponding characteristics. If a property is sold for a price above the median considering the year, size, and building year, it is matched with the rent estimate for properties with both central heating and an own bathroom. Conversely, if a property is sold for a price below the median, it is matched with the rent estimate for properties with either an own bathroom or central heating. In this case the results are also hold through.

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Chapter 3

Urban Spatial Distribution of Housing Liquidity*

Joint with Mark Toth and Jonas Zdrzalek

3.1 Introduction

Housing markets are local, with little of the variation in house prices being explained by national factors alone. As a result, housing markets are often modeled within spatial equilibrium frameworks in which local market conditions determine prices (Alonso, 1964; Roback, 1982). Housing markets also involve bilateral transactions, typically characterized by significant informational and search frictions (Han and Strange, 2015).

In this paper, we investigate how local market conditions interact with trading frictions. We demonstrate that in urban settings, the cost of travelling to the city center determines both the demand for housing services and local market thickness, thereby simultaneously generating. price and liquidity gradients. Similar to liquidity premiums observed in bond and stock markets (Amihud and Mendelson, 1986), we identify and quantify a liquidity premium for properties in city centers compared to those in the outskirts. We conclude that taking into account the interaction between local market conditions and trading frictions significantly enhances our understanding of the factors driving the spatial variation in house prices.

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Our knowledge about the spatial variation in housing liquidity is still limited, as detailed data on housing market transactions, especially with measures of liquidity, is scarcely available. Using a novel data set that combines the universe of real estate transaction contracts and advertisements for apartments in large German cities over the last decade, we provide evidence that housing market liquidity and prices jointly decrease with distance to the city center. Even after controlling for a large set of property characteristics, we find that apartments located farther from the city center take longer to sell and have lower prices.

We then develop a theory to study the effects of location on prices and liquidity. We build a spatial search model of housing within a monocentric city to show how the distance to the city center can affect both the value and the liquidity of housing. The cost of travelling to the city center impact both the demand for housing services and local market thickness. Sellers face a lower expected demand outside the city center, which increases the expected time on the market and decreases house price. We thus show how travel costs can simultaneously explain why prices and liquidity drop with distance to the city center. Using our transaction-level liquidity data, we calibrate the model and are replicate the joint spatial distribution of house prices and liquidity for all cities in our sample with a high degree of certainty.

As hypothesized by Amihud and Mendelson (1986), the discounted value of transaction costs serves as a proxy for the value loss attributed to illiquidity. Consequently, given a certain utility derived from residing in a house, we anticipate that greater illiquidity would correspond to a reduction in its price. However, liquidity is influenced by the house's location, which also affects its fundamental value. Therefore, in order to isolate the effects of liquidity on prices, we require structural estimation. First, we determine the welfare-maximizing allocation by removing search frictions in our model. Comparing the price gradients with and without search frictions allows us estimate a liquidity premium for housing in the city center vis-a-vis the outskirts. On average, across cities and using different discount factors for robustness, we estimate this liquidity premium to be 8% in terms of the house price in the city center.

In our empirical study, we analyze the spatial distribution of housing liquidity. To achieve this, we match housing advertisements with transactions using a nearest-neighbor algorithm. We obtain a dataset at the transaction level with geocoded information on housing liquidity, covering four large German cities, Hamburg, Cologne, Frankfurt, and Duesseldorf, from 2012 to 2022. To work with a sample that has consistent coverage across space, we focus our analysis on residential apartments.

We measure the time an apartment spends on the market as the number of weeks the advertisement for this apartment remains online. We start by showing that apartments closer to the city center spend less time on the market. However, housing characteristics in the outskirts differ significantly from those in the inner city. We take these differences into account by controlling for characteristics such as apartment size, building age, or number of bathrooms. The effect magnitude is consistent across cities. Every additional 3 kilometers of distance to the city center prolong the time on the market by 1 week on average.

We demonstrate the robustness of our findings in various alternative specifications. For example, we use an alternative measure of liquidity, the gap between asking and sales prices, and an alternative measure of distance, the travel time to the city center. Furthermore, we show that location is the primary determinant of housing liquidity, even though other aspects of properties also predict housing liquidity.

We rationalize our empirical results within a spatial search model in which a city's frictional housing market clears simultaneously via prices and liquidity. We borrow our notion of space from the monocentric city model in which house prices depend on travel costs to the city center and, consequently, the location of housing units (Alonso, 1964; Mills, 1967; Muth, 1969). We introduce a search mechanism which gives rise to liquidity differentials within the city, building on Krainer (2001). According to our model, liquidity and prices jointly decrease with distance to the city center because buyers are less likely to purchase apartments due to increasing travel costs to the city center. To explain these spatial gradients in detail, we propose the following mechanism.

Buyers search for apartments across the city. The further away an apartment is located from the city center, the higher are the travel costs associated with this property. When deciding whether to buy apartments, buyers want to be compensated for these travel costs. They require higher draws of utility shocks, which represent buyers' idiosyncratic valuation of apartments, the farther an apartment is located from the city center. This results in a lower probability of sale. As a result, the expected time on the market increases with distance to the city center, which results in a negative spatial liquidity gradient.

Sellers, being local monopolists at the distance to the city center at which their apartments are located, then face higher expected demand in the city center. Accordingly, they set higher prices in the city center relative to the outskirts, which gives rise to a negative spatial price gradient.

We calibrate the model using our transaction and advertisement data. For each city, our model only requires information on the average holding period, the average price, the average time on the market, and travel times to the city center. Even though we do not target any equilibrium spatial gradient in the calibration, our model is able to match the spatial price and liquidity gradients from our transaction and advertisement data for all cities with high precision.

Using our calibrated model, we estimate a liquidity premium for apartments in the city center relative to the outskirts. We think of the liquidity premium in the city center relative to some location as the relative price difference in scenarios with search frictions versus without search frictions. We find that the liquidity premium in the in the city center relative to the outskirts amounts to about 8% to 10% of the house price in the city center. Across cities and discount factors between 0.93 and 0.97, the average spatial liquidity premium is 9%. Furthermore, by comparing the model-implied price gradients with and without search frictions with the price gradient from the data, we find that spatial liquidity differences due to search frictions explain about a third within-city spatial price gradient.

This paper adds to the extensive body of research on the determinants of housing prices. While previous studies have mainly investigated how location affects the value of land or housing services (for recent studies, see, e.g., Albouy, Ehrlich, and Shin, 2018; Gupta et al., 2022; Liotta, Viguié, and Lepetit, 2022), we show that location also plays a role in determining housing liquidity. In doing so, we document an urban housing liquidity gradient, which adds to the well-documented urban price gradient (for an overview, see Duranton and Puga, 2015). From the empirical perspective, a closely related paper is Ruf (2017) which measures liquidity gradients in Swiss rental markets, but the focus is on the implications for investors. By estimating the spatial structure of the housing liquidity premium, we contribute to the literature on liquidity and asset prices, which has mostly been focused on stock and bond markets (Amihud, Mendelson, and Pedersen, 2012), but also includes studies on housing markets (Lin and Vandell, 2007; He, Wright, and Zhu, 2015).

By incorporating a spatial equilibrium in a housing search model, we extend current theoretical frameworks of trading frictions in housing markets (see Han and Strange, 2015), making them more capable of explaining spatial patterns of prices and liquidity. Duffie, Gârleanu, and Pedersen (2005) model liquidity in over-the-counter markets via a search framework. Whereas they focus on sales opportunities for sellers and hence the supply side, we focus on the demand side, as we provide arguments for liquidity differentials across space due to travel costs to buyers. Cai, Gautier, and Wolthoff (2024) distinguish locations in a spatial search model that is not specific to the housing market via chances for sellers of meeting buyers. They specifically consider the location choice of sellers. In the housing market, locations of sellers are fixed, and we take the spatial distribution of sellers, expressed in distances to the city center, as given.

Our work also contributes to the emerging field of urban finance (e.g., Favilukis, Mabille, and Van Nieuwerburgh, 2023) which analyses the role of risk and trading frictions in settings in which location matters for asset prices. Furthermore, we add to the growing body of literature on regional differences in housing markets. While these papers had focused on documenting and explaining differences in housing liquidity across regions (Amaral et al., 2021; Vanhapelto and Magnac, 2023; Jiang, Kotova, and Zhang, 2024), we are the first to document within-city patterns and derive their implications for housing liquidity premiums.

The rest of this paper is organized as follows. Section 2 describes our data and defines our measures of space and liquidity. Section 3 presents our empirical analysis. Section 4 describes our model framework and presents our analytical and quantitative results. Section 5 concludes.

3.2 Data & Measurement

In our empirical analysis, we use two novel data sets on urban housing markets in Germany, one of which is derived from administrative records of housing transactions, and another one which is derived from housing market advertisements. The transaction data gives us information on sales prices. The advertisement data gives us information on advertisement duration from which we obtain our measure of time on the market. From each data set, we only select apartments for our analysis, which allows us to investigate the role of location consistently within a city, as other types of residential housing are typically scarce in the city center. We match the two data sets for our empirical analysis via a nearest-neighbor algorithm.

3.2.1 Transaction data

Data description. We obtain the transaction data from a novel data set that covers the universe of residential real estate transactions in large German cities for several decades. This data source is introduced and described in detail in Amaral et al. (2023). The authors of this paper compile data from public local real estate committees (*Gutachterausschüsse*). Collecting information on all real estate transactions from notaries, the real estate committees register information on sales prices, contract dates, addresses and precise information on location in the form of coordinates, and various property characteristics.

Data cleaning. We clean the transaction data by filtering out property sales between relatives, leaseholds, package sales involving multiple properties sold together, sales of social housing, foreclosures, and any other sales flagged by the real estate committees as not aligning with genuine market prices. We remove outliers from the sample by excluding transactions of properties with prices or sizes above the 99th percentile or below the 1st percentile within a given year.

3.2.2 Advertisement data

Data description. We obtain data on apartment advertisements via *VALUE Marktdaten*, who collect and processes real estate advertisements from online platforms and real estate agencies.[1] We observe the dates on which the ad was posted and removed, addresses and coarse information on location such as zip code or neighborhood, asking prices, and various property characteristics. The data set covers the period between January 2012 and December 2022.

1. We are very grateful to Sebastian Hein from *VALUE Marktdaten* for giving us access to the data and support throughout the process of writing the paper.

Data cleaning. A common issue with online real estate advertisement data is the presence of multiple advertisements for the same property. *VALUE Marktdaten* has developed and implemented an algorithm to identify and exclude duplicates, and as such, this is not an issue in our data cleaning process. We remove outliers by excluding advertisements of properties with asking prices or sizes above the 99th percentile or below the 1st percentile within a given year.

3.2.3 Matching transactions and advertisements

We analyze liquidity and price patterns across space. The transaction data gives us information on sales prices and the location of apartments, while the advertisement data gives us information on liquidity via the advertisement duration. To prepare our analysis, we match the two data sources by applying a nearest-neighbor algorithm, such that we can associate a sales price and a set of coordinates from the transaction data with a marketing time from the advertisement data. The nearest-neighbor algorithm matches observations from the two data sets by considering locations, contract dates, advertisement dates, and property characteristics. Our goal is to uniquely associate transactions with advertisements. However, we do not observe advertisements for all transacted properties and are therefore only able to match a subset of the universe of transactions with corresponding advertisements.

Matching algorithm. The algorithm starts by matching observations with complete addresses, that is, addresses which include house numbers and street names. However, for apartments, having information on solely the house number and street name is insufficient for a successful match, as there may be multiple apartment transactions related to the same building. If that is the case, the algorithm excludes ads based on property characteristics if they meet the following criteria, in the given order:

(1) The living area differs by more than 10%.
(2) The floor number differs by more than 2.

We choose these apartment characteristics since they have the lowest number of missing values from the set of variables that are covered by both data sets.[2] We choose the numeric values for the criteria such that we have reasonable buffers for measurement errors due to incorrect user inputs. If, after applying these criteria, there are still multiple potential ads remaining, the algorithm selects the ad that

2. When we match based on the building's exact address, we do not exclude matches with different building years. Matching by address is sufficient to identify a building, and typically, the building year is the same for all flats within a building. When this is not the case, we attribute the different building years to measurement error, that is, incorrect user-specified information on the advertisement websites.

minimizes the distance to the transaction in the aforementioned characteristics.[3] We match the transactions which do not have entries with complete addresses via the same process as for those with complete addresses, but condition sequentially on the following geographical objects: street name, zip code, and neighborhood (*Stadtteil*), until we have a unique match. If there is no unique match, we drop the observation.

Data cleaning. We exclude observations that contain implausible information on the sequence of market events. First, we exclude advertisements that were published after the contract date of the transaction. Second, we exclude ads that were removed more than one year before the contract date. A time span of more than one year between the end of the advertisement and the contract date is unlikely. On average, we match and keep about 30% of the transactions across cities. In Table 3.1, we provide further information on the matched observations by city.

Table 3.1. Summary statistics: matched data set

City	# Transactions	# Ads	# Matched	Avg. sales price (€)	Avg. asking price (€)
Hamburg	74030	69399	22964	401461.5	400359.1
Cologne	35597	41505	14188	236154.3	249582.1
Duesseldorf	34732	30253	10565	304701.5	317618.8
Frankfurt	32828	34171	14696	380930.7	437007.4

Note: This table reports summary statistics about the matched transaction and advertisement data for the period January 2012- December 2022.

3.2.4 Measurement of spatial variables

We measure spatial variation in our data using a single variable, the kilometer distance to the city center, an established measure in the urban economics literature (see e.g., Duranton and Puga, 2015). We obtain this distance via the coordinates of the city centers and the coordinates of the matched apartments. We select the *Alsterhaus*, a historic shopping quarter, as the city center of Hamburg. For Cologne, we select the Cologne Cathedral (*Kölner Dom*). For Frankfurt, we select the *Willy-Brandt-Platz* and for Duesseldorf, we select the *Marktplatz*. We select these city centers as they are located in the historical centers of these cities. In a robustness check, we show that selecting the centroid of the commercial district with the highest land value (via the *Bodenrichtwerte* land value measurements from the *Gutachterausschüsse* real estate committees) yields almost identical city centers as the ones we choose by hand.

3. We minimize the absolute difference between the value from an advertisement and the value from the transaction. If this difference is the same for the apartment size, we proceed with the difference in the floor number. If the algorithm still does not yield a unique match, we drop the observation.

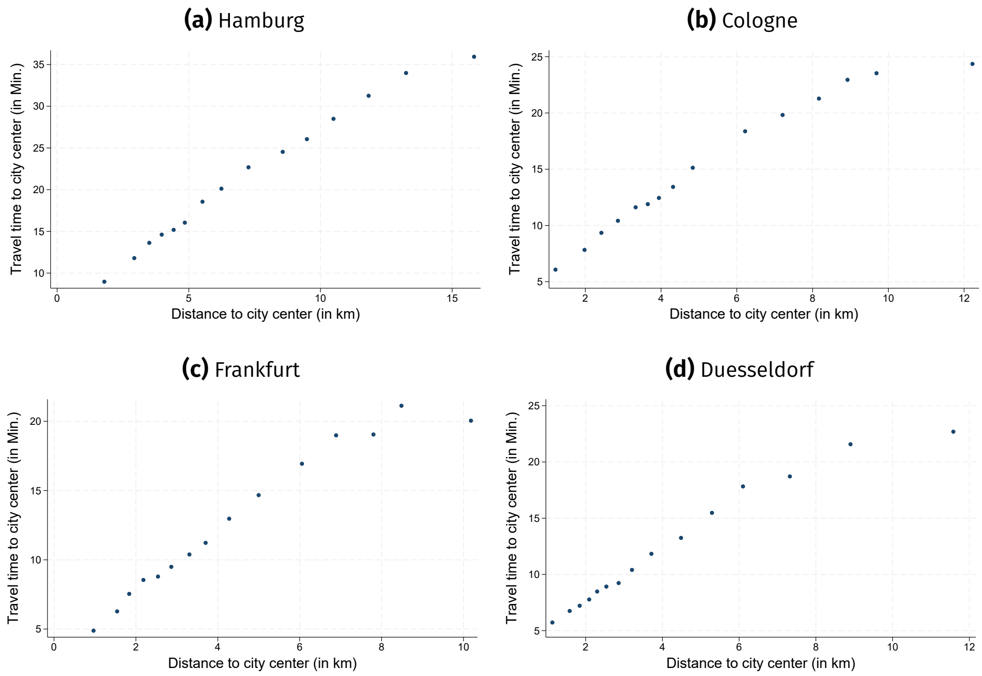

Figure 3.1. Travel time to the city center (January 2012- December 2022)

Note: This figure shows the travel time by car to the city centers of Hamburg (*Alsterhaus*), Cologne (Cologne Cathedral), Frankfurt (*Willy-Brandt-Platz*), and Duesseldorf (*Marktplatz*), in terms of the kilometer distance from the respective city center.

As an alternative spatial measure, we use travel time estimates. The spatial structure of cities can feature rivers or other factors that influence local transportation. Such features can be more accurately represented via the travel time rather than the kilometer distance to the city center. Via an API provided by Openrouteservice, we request the typical travel time to the city center by car for each apartment in our matched data set. We summarize the resulting travel time estimates in Figure 3.1, using 15 bins with equal numbers of observations.

3.2.5 Measurement of liquidity

We measure housing market liquidity via the time on the market of apartments, a measure typically used in the literature (Han and Strange, 2015). We define the time that a property stays on the market as the number of weeks between the start and the end of an advertisement.[4] The time spent on the market of apartment i sold in period t is

$$\mathrm{TOM}_{it} = \frac{\text{Number of days advertised}_{it}}{7}, \tag{3.1}$$

where an apartment is defined to have been on the market for $T/7$ weeks if it sells on day number T of being advertised. In Figure 3.2, we plot histograms of our time on the market measurements.

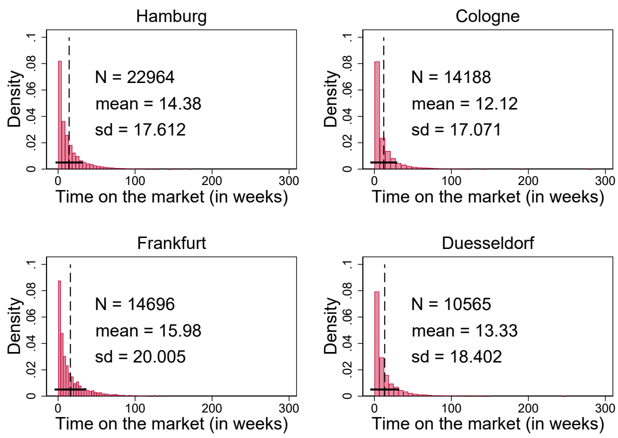

Figure 3.2. Histograms of time on the market (January 2012- December 2022)

Note: This figure shows histograms for the time on the market, as defined in (3.1), in our matched data set.

3.3 Empirical results

3.3.1 Liquidity decreases with distance to city center

Visual exploration. Figure 3.3 shows maps with estimates of the average liquidity by district (*Stadtteil*) in Hamburg, Cologne, Frankfurt, and Duesseldorf. In all cities, the time on the market is lowest in the city center and increases with distance to the city center. Close to the city center, apartments stay on the market for about 11 weeks. In the outskirts, apartments stay on the market for about 16 weeks.

4. We define the start and end dates of the advertisement as the start and end dates of the time an apartment is on the market. By doing so, we make the assumption that the ad is removed when the seller and the buyer reach an agreement. While we cannot confirm this assumption, there are indications that buyers have strong incentives to ensure the property is taken off the market promptly upon reaching an agreement with the seller (see e.g., Vanhapelto, 2022).

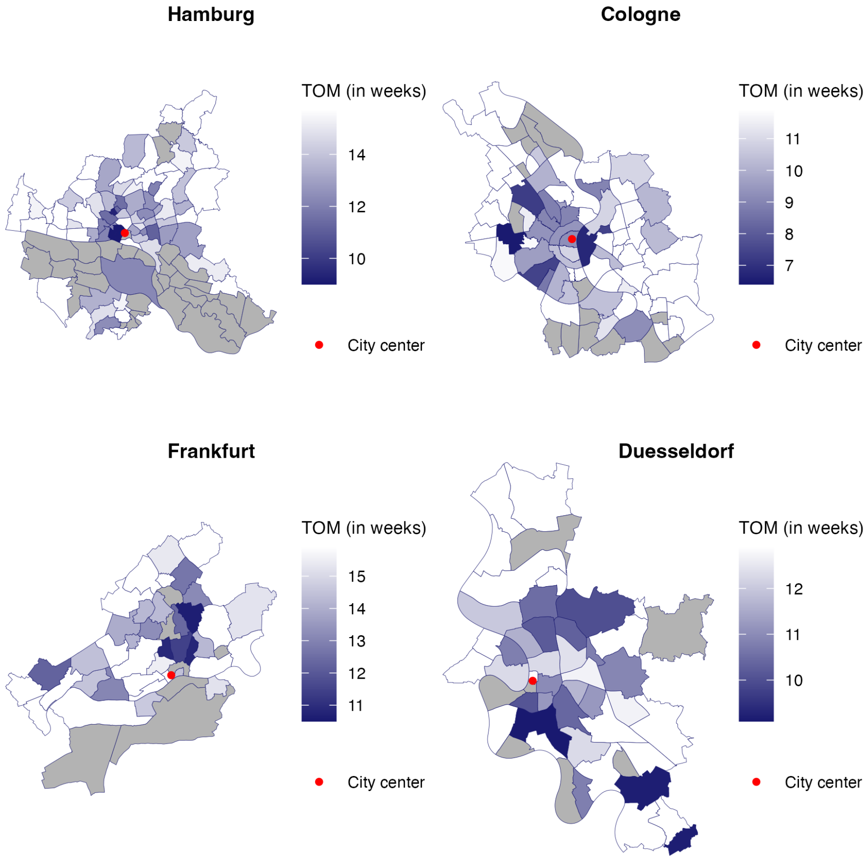

Figure 3.3. Time on the market across space (January 2012- December 2022)

Note: The maps show the average time on the market as defined in (3.1) by district (*Stadtteil*) from our matched data set, controlling for year-quarter fixed effects. Districts without available data are colored gray.

Regression framework. We want to rule out that these patterns are driven by systematic spatial variation in apartment characteristics. For example, smaller apartments, which are typically traded more easily, are located mostly in the city center.[5] We estimate the association between time on the market and distance to the city center for each city separately via the regression specification:

$$\text{TOM}_{it} = \alpha \cdot \text{distance}_i + \beta \cdot X_i' + f_t + \varepsilon_{it}, \tag{3.2}$$

where i indexes apartments and t indexes the year-quarter of transaction, the distance on the right hand side is the kilometer distance to the city center in our base-

5. For an overview of the quantitative influence of such characteristics on liquidity, see e.g., Forgey, Rutherford, and Springer (1996), Anglin, Rutherford, and Springer (2003), Carrillo (2012), or Hayunga and Pace (2019).

line specification and the travel time to the city center (in minutes) in our alternative specification, X_i is a vector of apartment characteristics,[6] f_t is a year-quarter fixed effect to account for common time trends in liquidity within a city, and ε_{it} is the error term.

Results. You can find our regression estimates in Figure 3.4. We run 4 specifications in which we use the kilometer distance as the right-hand-side variable without and with controls and the travel time as the right-hand-side variable without and with controls. All our estimates are significant at the 1% level and their economic magnitudes are approximately equal across cities. About 3 additional kilometers of distance to the city center correspond to an additional week on the market. In terms of travel time, about 6 more minutes of car travel time correspond to an additional week on the market. These estimates are sizable, given that the average time on the market is about 14 weeks across cities, and they are almost identical across cities. The repeated pattern calls for a theory which we develop in the second part of the paper. Before doing so, we provide some additional empirical results.

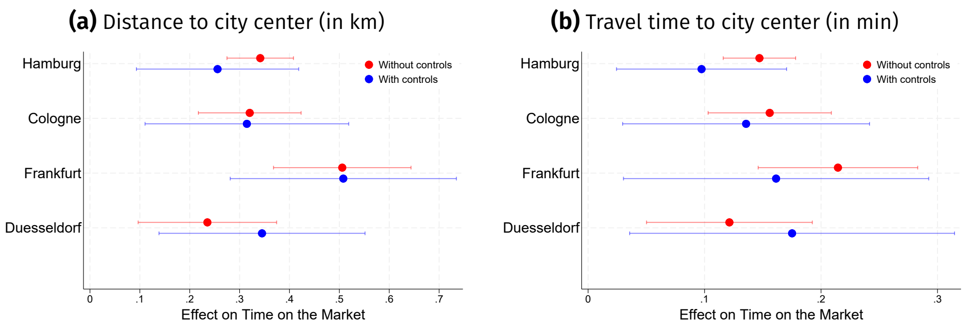

Figure 3.4. Effect of distance to city center on time on the market (January 2012- December 2022)

Note: These figures show the OLS regression coefficients of distance to the city center as specified in (3.2) with 99% confidence intervals. All regressions include year-quarter fixed effects. See Footnote 6 for a full list of apartment characteristics controls.

3.3.2 Sales prices decrease with distance to city center

As an addition to our novel empirical findings, we reproduce a standard finding from the urban economics literature. The monocentric city model predicts a

6. We control for the following variables: living area in m^2, living area squared, number of rooms, year of construction, "Altbau" or not, "Neubau" or not, physical condition of the building, whether the apartment is in the upper floor of the house or not, whether the apartment is rented out or not, type of heating (e.g., central heating), source of heating (e.g., gas), whether the apartment has a fitted kitchen or not, whether the apartment has an open kitchen or not, whether the bathroom has a shower, whether the bathroom has a bathtub, whether the apartment has a terrace or balcony, whether the apartment has a basement, whether the apartment has a garden, and the number of parking spaces.

negative spatial price gradient, which is typically tested empirically with prices in logarithms and distances in levels (Duranton and Puga, 2015). We run regression specification (3.2) with log sales prices as the outcome variable and plot the resulting binscatter plots in Figure 3.5. Our results align with the standard findings.

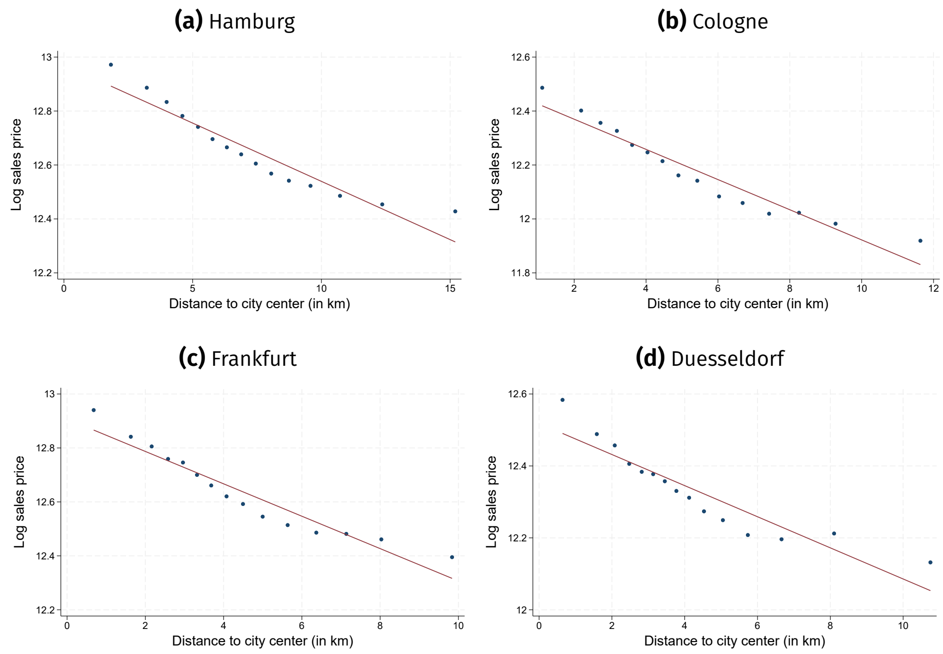

Figure 3.5. Spatial gradients of sales price (January 2012- December 2022)

Note: These binscatter plots visualize the results of regression (3.2) with log sales price as the outcome variable and 15 equally-sized distance bins. The regressions include year-quarter fixed effects and control for apartment characteristics listed in Footnote 6.

3.3.3 Discussion of external validity

We cannot be sure if we are able to transfer our findings to other cities. The negative spatial price gradient has been observed in monocentric cities of different sizes across the globe (Liotta, Viguié, and Lepetit, 2022). If the spatial price gradient is the result of the same economic mechanism as the liquidity gradient, we should be able to generalize our findings about liquidity similarly. In our theoretical framework, we argue that travel costs to the city center give rise to such a mechanism.

Our findings are not transferable to non-monocentric cities. The most established deviation from the monocentric city model is the polycentric city model[7] with Chicago as a classic example (McMillen and McDonald, 1997). We view our findings as applicable to typical monocentric cities and make no statement about spatial liquidity patterns in cities with different structures.

7. Other non-monocentric models of cities are, for example, the maximum disorder model, the mosaic of live-work communities model, and the constrained dispersal model (Angel and Blei, 2016).

3.3.4 Robustness analysis

Unsuccessful ads. Our baseline analysis is based on the data set of matched ads. Our results could be biased if the number of ads that did not end up in a sale varies systematically across space. To check this, we run an algorithm to identify the ads that do not end up in a transaction.

We identify ads that did not result in a sale via three steps. First, we match all ads with transactions that occurred within the same neighborhood. Each ad is then associated with a set of potential transactions in the neighborhood. Out of these ads, we identify those as "unsuccessful" that are associated with transactions one year after or before the ad was published. Second, we identify ads as "unsuccessful" that are associated with transactions for which the living area of the matched apartment differs by more than 40%. Finally, we identify ads as "unsuccessful" for which the remaining potential matches have a living area, building year, and floor number that deviate by more than 10%, 10 years, and 2.

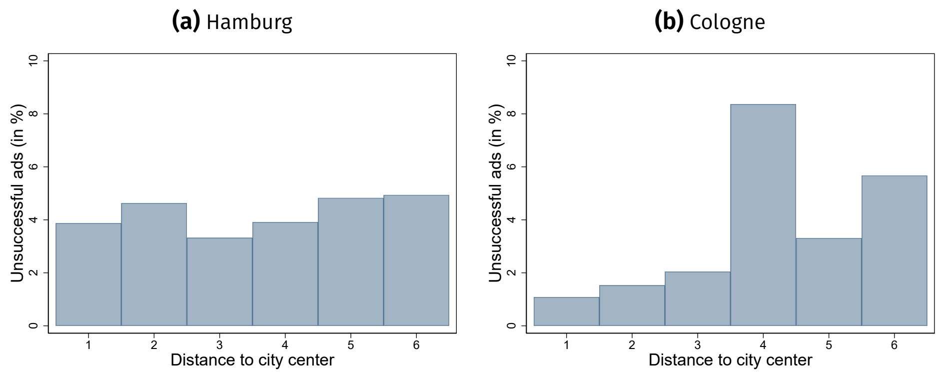

Figure 3.6. Unsuccessful ads and distance to the city center

Note: These figures display the percentage of ads that do not result in a sale by distance to the city center with 6 equally-sized distance bins.

Figure 3.6 plots the percentage of ads that did not result in a sale and shows that this percentage is increasing with distance to the city center. To further quantify this relation, we run a survival analysis using the combined dataset of successful and unsuccessful ads and find that the probability of an ad not resulting in a sale increases with distance to the city center. We display these results in Appendix 3.B. Note that to the best of our knowledge, it is a novel contribution in this paper to identify the ads that result in a sale.

Asking price discount. One potential explanation for the time on the market to be increasing with distance to the city center is that sellers in the city center systematically accept bids below their asking prices, thus accelerating the sale. To check this, we measure the relative spread between the asking price[8] and the transaction price for property i sold in period t, which we define as the asking price discount:

$$\text{Discount}_{it} = 100 \cdot \frac{(\text{Sales price}_{it} - \text{Asking price}_{it})}{\text{Asking price}_{it}}. \tag{3.3}$$

A more negative or less positive discount corresponds to lower liquidity. We find that this spread is generally negative and becomes more negative with distance to the city center. Hence, sellers in the city center can expect a lower time on the market and a final sales price which is closer to the original asking price. We display these results in Appendix 3.B.

Temporal variation. Our analysis covers the period between 2012 and 2022. We check whether our results are driven by a specific time interval by running regression (3.2) on a rolling-window basis to get time-varying coefficients. The coefficients are positive in every period and significant at the 99% confidence level in almost every period (see Figure 3.7). The coefficient sizes are roughly constant over time in every city except for Cologne, where they drop in the second half of the sample.

Include unmatched ads. Our matching procedure is conservative, as we try to only keep matches which we consider to be correctly identified with a high degree of certainty. It could, nevertheless, be the case that we are systematically excluding observations that would counteract our findings. To check this, we run regression (3.2) using the complete sample of ads. Figure 3.8 shows that this specification hardly influences our results.

Alternative regression specifications. By definition, the time on the market is positive and as such, a standard OLS regression might not be optimal to use. As we show in Appendix 3.B, our results hold in Poisson regressions and OLS regressions with logarithmic time on the market.

8. We observe two asking prices in the data: the asking price on the day the ad was initially posted and the asking price on the day the ad was taken down. Our results hold with both of these two asking prices in the calculation of the asking price discount. For simplicity, we only use the asking price on the day the ad was taken down.

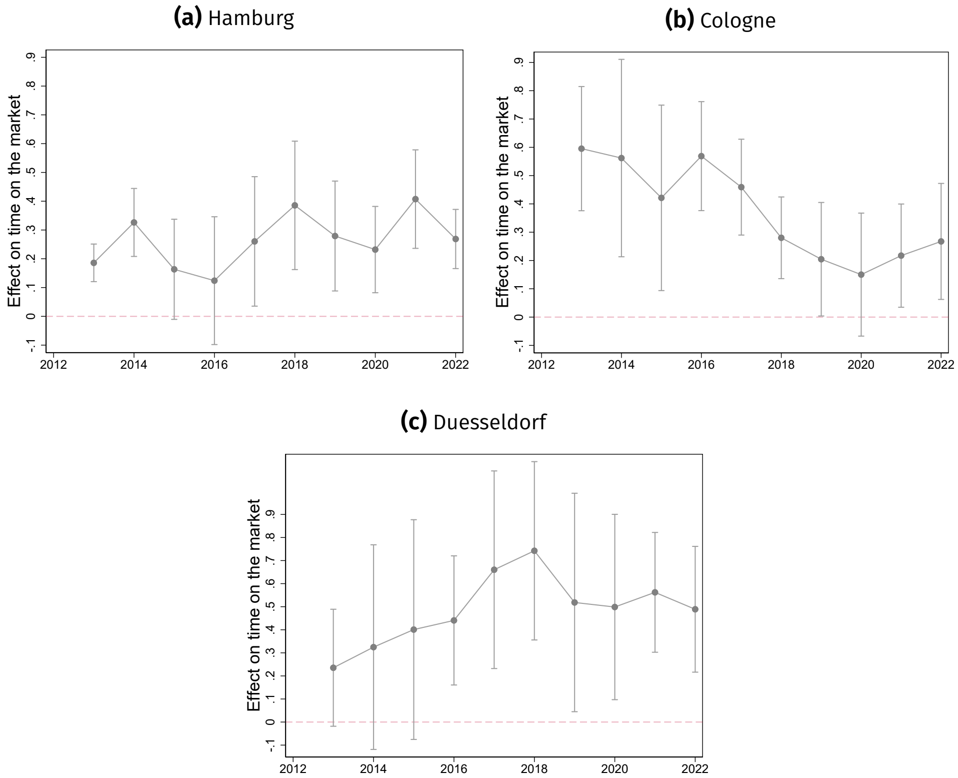

Figure 3.7. Effect of distance to the city center on time on the market over time (January 2012–December 2022)

Note: These figures plot the coefficients of regression specification (3.2) for the time on the market as defined in (3.1) over time. The coefficients are based on rolling-window regressions with year-quarter fixed effects and apartment characteristics controls listed in Footnote 6.

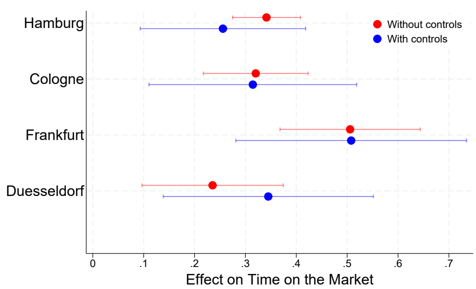

Figure 3.8. Effect of distance to city center on time on the market using all ads (January 2012-December 2022)

Note: These figures show the OLS regression coefficients of distance to the city center as specified in (3.2) with 99% confidence intervals, using a sample with matched an unmatched ads. All regressions include year-quarter fixed effects. See Footnote 6 for a full list of apartment characteristics controls.

3.4 Model

3.4.1 Model setup

3.4.1.1 Overview

We rationalize the empirical facts documented in the previous section by deriving analytical relations between liquidity and distance to the city center in a spatial search model of a city's housing market. Moreover, we show that our model can account for the patterns we observe in the data quantitatively by calibrating the model using our transaction and advertisement data.

We start from a standard housing search model by Krainer (2001) in which housing market clears via prices and liquidity, given by the expected time on the market. To introduce a notion of space, we rely on the monocentric city model (Alonso, 1964; Mills, 1967; Muth, 1969) and measure the distance to the center within a symmetric city. The spatial distribution of housing in the monocentric city model is endogenous. In our model, we take the spatial distribution of housing as exogenously given and do not impose symmetry on the city structure. We abstract from migration between cities.

3.4.1.2 Theoretical framework

Time, agents, and city. Time is discrete and runs forever. A time period equals one day. We focus on a stationary equilibrium and omit time indices. A large number I of infinitely-lived, financially unconstrained agents live in a city. The agents are risk-neutral and discount with a common factor $\beta \in (0,1)$.

The city has a single city center to which all agents travel every period for work or leisure activities.[9] Agents pay travel costs $\tau(d)$ at distance to the city center d per period, where $\frac{\partial \tau}{\partial d} > 0$ and the distribution of distances is denoted by $\mathcal{D}$. Apart from determining agents' travel costs, space has no economic significance.

Housing. The housing stock is exogenously given by I identical fixed-size apartments. Each apartment is characterized by its distance to the city center d. In the first model period, every agent lives in an apartment. In every period, a match between an agent and an apartment persists with probability π. With probability $1-\pi$, an agent has to move out, put their apartment up for sale, and search for a new apartment. Then, the agent acts as a buyer and as a seller simultaneously.

9. In principle, we do not have to assume that agents only travel to the city center. It would be sufficient to assume that jobs and/or leisure activities are concentrated in the city center, such that the city center is the focus of travel within the city. For simplicity, we assume that agents only travel to the city center, which allows us to translate straightforwardly between travel time to the city center in minutes and travel costs $\tau(d)$ in the calibration.

Risk neutrality of agents implies that we can analyze buyer and seller decisions separately.

Before purchasing an apartment, an agent draws a uniformly distributed[10] idiosyncratic housing dividend $\varepsilon \sim U[\tilde{\varepsilon}-1, \tilde{\varepsilon}]$ for this apartment. If they decide to purchase the apartment, they receive this dividend in every period until they are unmatched. The dividend is identically and independently distributed across agents, distances to the city center, and time periods. An agent can only occupy one apartment at a time and can only search for new apartments after they have been unmatched with their old apartment.

While searching for apartments, agents live in the city center in rental units owned by risk-neutral investors from outside the city. Thus, searchers do not incur travel costs and pay rental costs that are equal to the value of their housing service flow, receiving zero net utility. Agents cannot rent out their owned apartments. The rental market is not modeled explicitly.

Search process. A buyer visits a random apartment of those that are currently on the market.[11] When visiting an apartment, the buyer observes their idiosyncratic valuation ε for this apartment and the apartment's distance to the city center d. The seller of the visited apartment posts a price $p(d)$ without observing the buyer's idiosyncratic valuation. The buyer either agrees on the posted price and moves into the apartment in the next period or does not agree on the posted price and continues to search.

Seller's problem. A seller maximizes their profits $\Pi(d)$ over a posting price $p(d)$. In the following, we denote by $\gamma(p(d))$ the probability that the apartment is sold, given that the seller posts a price $p(d)$. The seller's profits for an apartment at distance d are

$$\Pi(d) \;=\; \max_{p(d)}\Big\{\gamma(\cdot)p(d) + (1-\gamma(\cdot))\beta\,\Pi(d)\Big\}. \tag{3.4}$$

With probability $\gamma(\cdot)$, the seller receives the amount $p(d)$. With probability $1-\gamma(\cdot)$, they try to sell the apartment again next period, and their discounted continuation value is $\beta\Pi(d)$. Sellers act as price setters. The probability of sale $\gamma(\cdot)$ reflects the expected demand at distance d, given a price $p(d)$. When optimizing, a seller takes

10. We use a uniform distribution for tractability and thus follow Krainer (2001). We normalize the boundaries of the distribution such that we only need to calibrate a single parameter for every city later in the quantitative exercise.

11. Search is random in this model. If buyers could choose where to search, they would search with higher intensity closer to the city center, where their ex-ante net utility is higher due to lower commuting costs. All else equal, liquidity would increase in the city center, which would steepen the liquidity gradient.

into account the effect of their posted price on the expected demand at the location of their apartment.

An agent can only occupy one apartment at a time, but can have multiple apartments on the market as a seller. Such a scenario occurs if an agent has to move out of an apartment and becomes a searcher, finds a new apartment to live in, but has not been able to sell their old apartment(s).[12]

Buyer's problem. A buyer who purchased an apartment at distance d receives the value

$$V(d,\varepsilon) \;=\; \beta\left(\varepsilon - \tau(d) + \pi V(d,\varepsilon) + (1-\pi)\left(\Pi(d) + W\right)\right), \tag{3.5}$$

where W denotes the value of search. Starting next period, the buyer receives the dividend ε and pays commuting costs $\tau(d)$. With probability π, the buyer keeps on living in the apartment for another period and receives the continuation value. With probability $(1-\pi)$, the buyer becomes unmatched and receives the sum of the value of the resale value $\Pi(d)$ the value of search W which is given by

$$W \;=\; E_{d,\varepsilon}\left[\max\left[V(d,\varepsilon) - p(d), \beta W\right]\right]. \tag{3.6}$$

Either the buyer accepts the posted price and receives $V(d,\varepsilon)$ while paying $p(d)$, or the buyer continues to search and receives βW. We assume that the expectation over distances is always formed using the whole distribution of distances $\mathcal{D}$, in other words, buyers do not know the distances of apartments that are on the market.

3.4.2 Equilibrium

Seller's optimization. The first-order condition of the profit function yields

$$p(d) \;=\; \beta\Pi(d) - \frac{\gamma(p(d))}{\partial\gamma/\partial p\;|_{p=p(d)}}, \tag{3.7}$$

where the derivative $\partial\gamma/\partial p$ is evaluated at the optimal posting price $p(d)$ at distance d. We prove that the solution of this first order condition provides the required maximum in the Appendix.

12. Following Krainer (2001) and Krainer and LeRoy (2002), we ignore the possibility that a single agent accumulates all houses over any finite time interval, in which case this agent would not be able to visit another house if their match fails.

Buyer's optimization. We define a reservation dividend $\varepsilon^*(d)$ at which a buyer is indifferent indifferent between buying an apartment and continuing to search:

$$V(d, \varepsilon^*(d)) - p(d) \;=\; \beta W. \tag{3.8}$$

The solution of this equation at a given distance to the city center characterizes the reservation dividend at this distance. A buyer purchases an apartment when they draw an idiosyncratic dividend that is larger than or equal to the reservation dividend at the apartment's distance to the city center. If they draw a smaller dividend, they continue to search.

Notion of spatial equilibrium. Equation (3.8) implies that a buyer must be indifferent between buying at different locations, as the left-hand side depends on the distance to the city center, whereas the right-hand side does not. The buyer indifference condition is hence also a *spatial equilibrium condition*. When facing the decision to accept or reject an offer, a buyer has to receive the same net utility (that is, the present value of occupying the apartment minus the price) at all distances to the city center.[13] In line with the interpretation of a spatial equilibrium in housing markets as a spatial no-arbitrage condition (Glaeser and Gyourko, 2008), there is no arbitrage opportunity for buyers across space.

Probability of sale. The equilibrium probability of sale at distance d is equal to the probability that a buyer's idiosyncratic dividend is above the reservation dividend at this distance:

$$\gamma(p(d)) \;=\; Prob(\varepsilon \;>\; \varepsilon^*(d)) \;=\; 1 - F(\varepsilon^*(d)) \;=\; \tilde{\varepsilon} - \varepsilon^*(d), \tag{3.9}$$

due to the uniform distribution of the idiosyncratic dividend. Thus, for the derivative in the seller optimality condition (3.7) we have that

$$\left.\frac{\partial \gamma}{\partial p}\right|_{p=p(d)} \;=\; -\left.\frac{\partial \varepsilon^*}{\partial p}\right|_{p=p(d)}. \tag{3.10}$$

13. This condition is analogous to typical spatial equilibrium conditions in urban economics. For example, in the Rosen (1979)-Roback (1982) model, agents choose in which city to live, given a rent and a wage in each city. In a spatial equilibrium, the difference between wage and rent must be equal across cities, since otherwise all agents would locate only in the city with the largest difference. Analogously, in our model, searchers are indifferent between accepting and rejecting offers at every location in equilibrium.

Rearranging the buyer's value function (3.5) yields

$$V(d,\varepsilon) = \frac{\beta\big(\varepsilon - \tau(d) + (1-\pi)(\Pi(d) + W)\big)}{1-\pi\beta}. \tag{3.11}$$

With indifference condition (3.8), we get

$$\varepsilon^*(d) = \frac{1-\pi\beta}{\beta}p(d) + \tau(d) - (1-\pi)\Pi(d) + (\pi - \pi\beta)W. \tag{3.12}$$

Hence,

$$\left.\frac{\partial\gamma}{\partial p}\right|_{p=p(d)} = -\frac{1-\pi\beta}{\beta}, \tag{3.13}$$

where $\frac{\partial\Pi}{\partial p}|_{p=p(d)} = 0$ due to the Envelope Theorem.

Equilibrium definition. A *stationary spatial equilibrium* consists of a seller profit function $\Pi(d)$, a price function $p(d)$, a value of search W, a reservation dividend function $\varepsilon^*(d)$, and a conditional sale probability function $\gamma(p(d))$ that satisfy equations (3.4), (3.6), (3.7), (3.8), (3.9) for all distances to the city center $d \in \mathcal{D}$, given a parameter vector $(\beta, \pi, \tilde{\varepsilon})$, a distribution of apartments' distances to the city center $\mathcal{D}$, and a travel cost function $\tau(d)$.

Additional remarks. We do not have a notion of market tightness in the model. Market tightness measures the relation between buyer intensity and seller intensity in the market and can be defined as the ratio of the number of buyers to the number of sellers. Papers that measure market tightness in housing markets typically use buyer online search behavior to approximate the number of buyers (e.g., van Dijk and Francke, 2018). We do not have such data available. Nevertheless, we can interpret our model setup to include relative differences in market tightness within the city, as buyers arrive at random apartments and decide whether to accept or reject offers. Implicitly, this yields a number of potential buyers at a given location, reflected by the probability of sale.

In the Appendix, we extend our model to include a bargaining process, following Carrillo (2012), and provide proofs of the equilibrium's existence, following Krainer (2001), and uniqueness, following Vanhapelto and Magnac (2023). Next, we derive analytical results that rationalize our findings from the empirical part of the paper. The purpose of deriving these results analytically is to show general properties of the model that hold regardless of the calibration.

3.4.3 Analytical results

We start with some auxiliary derivations to get to our main theoretical result, which is that the equilibrium expected time on the market increases with distance to the city center while the equilibrium sales price decreases with distance to the city center.

3.4.3.1 Reservation dividends across space

Lemma 3.1 shows that the buyer reservation dividend is increasing with distance to the city center. In other words, buyers need higher draws of the idiosyncratic dividend to make a purchase the further the apartment they visit is away from the city center. This buyer preference reflects the presence of commuting costs $\tau(d)$, for which buyers want to be compensated with higher idiosyncratic dividend draws.[14]

Lemma 3.1. *The reservation dividend $\varepsilon^*(d)$ increases with distance to the city center d.*

Proof. To show that the reservation dividend increases with distance to the city center, we express it in terms of the travel cost $\tau(d)$, the only variable that exogenously varies across space. We know from (3.12) that

$$\varepsilon^*(d) \;=\; \frac{1-\pi\beta}{\beta}p(d) + \tau(d) - (1-\pi)\Pi(d) + (\pi - \pi\beta)W.$$

We reformulate the asking price $p(d)$ and the profits from reselling the apartment $\Pi(d)$ in terms of the reservation dividend $\varepsilon^*(d)$. Combining the seller optimality condition (3.7) and the expression for profits (3.4) evaluated at the equilibrium price, we obtain

$$p(d) \;=\; -\frac{(1-\beta)\gamma(\cdot) + \beta\gamma^2(\cdot)}{(1-\beta)\partial\gamma/\partial p \;|_{p=p(d)}}. \tag{3.14}$$

With the equilibrium relations (3.9) and (3.13), we get

$$p(d) \;=\; \frac{\beta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon^*(d)) + \frac{\beta^2}{(1-\beta)(1-\pi\beta)}(\tilde{\varepsilon} - \varepsilon^*(d))^2. \tag{3.15}$$

14. In the calibrated model, travel costs do not necessarily have to increase with distance to the city center. If that were the case, the following propositions would not apply for the distances to the city center that correspond to the non-increasing part of the travel cost function. In practice, we rarely encounter such cases.

Using the seller optimality condition (3.7), profits are then

$$\Pi(d) = \frac{\beta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon^*(d))^2. \tag{3.16}$$

Thus, we can express the reservation dividend as

$$\begin{aligned}\varepsilon^*(d) = {} & \frac{1-\pi\beta}{\beta}\left(\frac{\beta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon^*(d)) + \frac{\beta^2}{(1-\beta)(1-\pi\beta)}(\tilde{\varepsilon} - \varepsilon^*(d))^2\right) \\ & + \tau(d) - (1-\pi)\left(\frac{\beta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon^*(d))^2\right) + (\pi - \pi\beta)W. \end{aligned} \tag{3.17}$$

We simplify and differentiate with respect to the distance to the city center d to obtain that

$$\frac{\partial \varepsilon^*}{\partial d}\underbrace{\left(2 - 2\frac{\pi\beta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon^*(d))\right)}_{>0} = \frac{\partial \tau}{\partial d}, \tag{3.18}$$

and therefore $\frac{\partial \varepsilon^*}{\partial d} > 0$, given that $\frac{\partial \tau}{\partial d} > 0$. □

3.4.3.2 Liquidity and prices across space

In line with the measurement of the time on the market in the empirical part of the paper, we define that an apartment has been on the market for T days if it sells on day number T. Via the expected value of the geometric distribution that results from the multiplication of sale probabilities over time, we have that the expected time on the market (in days) at a given distance to the city center d is

$$E[TOM(d)] = \frac{1}{\gamma(p(d))}. \tag{3.19}$$

Proposition 1. The expected time on the market $E[TOM(d)]$ increases with distance to the city center d.

Proof. Using the equilibrium relation between reservation dividends and probabilities of sale (3.9), we can express the expected time on the market in terms of the reservation dividend:

$$E[TOM(d)] = \frac{1}{\tilde{\varepsilon} - \varepsilon^*(d)}. \tag{3.20}$$

The derivative of the expected time on the market with respect to the distance to the city center amounts to

$$\frac{\partial E[TOM]}{\partial d} = \left(\tilde{\varepsilon} - \varepsilon^*(d)\right)^{-2}\frac{\partial \varepsilon^*}{\partial d} > 0 \tag{3.21}$$

if $\partial \varepsilon^*/\partial d > 0$. We know that this holds from Lemma 3.1. □

Intuition. Reservation dividends increase with distance to the city center, which reflects compensation for travel costs. Hence, probabilities of sale decrease with distance to the city center. A lower probability of sale implies a higher expected time on the market by definition.

Proposition 2. The sales price $p(d)$ decreases with distance to the city center d.

Proof. Via (3.15) from Lemma 1, we have that

$$p(d) = \frac{\beta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon^*(d)) + \frac{\beta^2}{(1-\beta)(1-\pi\beta)}(\tilde{\varepsilon} - \varepsilon^*(d))^2. \tag{3.22}$$

Then, with $\partial\varepsilon^*/\partial d > 0$,

$$\frac{\partial p}{\partial d} = \underbrace{\frac{\beta}{1-\pi\beta}}_{>0}\underbrace{\left(-\frac{\partial\varepsilon^*}{\partial d}\right)}_{<0} + \underbrace{\frac{2\beta^2(\tilde{\varepsilon} - \varepsilon^*(d))}{(1-\beta)(1-\pi\beta)}}_{>0}\underbrace{\left(-\frac{\partial\varepsilon^*}{\partial d}\right)}_{<0} < 0. \tag{3.23}$$

□

Intuition. Sellers expect to sell apartments with a lower probability outside the city center, where they face a lower expected housing demand. Being local monopolists, they find it optimal to post lower prices outside the city center.[15] As in the standard monocentric city model, the underlying factor for prices to decrease with distance to the city center is the cost of travel to the city center.

3.4.4 Solution method

We have established analytically that our model rationalizes the empirical patterns of decreasing liquidity and prices with distance to the city center. These statements are qualitative. We are not able to solve the model in closed form, as we obtain a nonlinear system of equations via the equilibrium conditions. Hence, we solve the model numerically. We show that our model performs well quantitatively by calibrating it with our data on transactions and advertisements.

15. Moreover, the sensitivity of prices to the probability of sale decreases with distance to the city center. Formally, via (3.14), we get the derivative of prices with respect to the probability of sale at a given location:

$$\left.\frac{\partial p}{\partial \gamma}\right|_{p=p(d)} = \frac{\beta}{1-\pi\beta} + \frac{2\beta^2}{(1-\beta)(1-\pi\beta)}\gamma(\cdot),$$

which decreases with distance to the city center.

Algorithm 1 Solution algorithm: stationary spatial equilibrium

Initialize an iteration tolerance η.
Initialize a value of search W.
Initialize an updated value of search $\tilde{W}$ with $|W - \tilde{W}| > \eta$.
while $|W - \tilde{W}| > \eta$ **do**
  Set $W = \tilde{W}$.
  for $d^{\Delta} \in \mathscr{D}^{\Delta}$ **do**
    Solve equations (3.4) to (3.9) for this distance d^{Δ}, given the value of search W.
  end for
  Update $\tilde{W}$.
end while

Setup. We discretize the distribution of distances to the city center: $\mathscr{D}^{\Delta} = \{d_1^{\Delta}, \ldots, d_l^{\Delta}\}$. The equilibrium condition (3.6), which describes the value of search as an expectation over distances to the city center and idiosyncratic dividends, and the equilibrium conditions (3.4) to (3.9), which have to hold for all distances to the city center $d^{\Delta} \in \mathscr{D}^{\Delta}$, constitute a system of non-linear equations. All variables in the system depend on the distance to the city center, except for the value of search W.

Solution algorithm. We solve the model using the solution algorithm described in the environment of Algorithm 1 to obtain the stationary spatial equilibrium. The algorithm iterates over the value of search W. It starts from a guess for the value of search and updates the guess using the expectation of searchers over the apartments they could match with before drawing a random apartment.[16] The algorithm stops when this expectation is consistent with the guess. We obtain our first guess for the value of search by solving the model without the spatial structure and using the value of search from that solution.

3.4.5 Calibration

We create the discretized distribution $\mathscr{D}^{\Delta}$ by grouping the distances to the city center from our apartment sales data into $l = 15$ bins with equal numbers of observations. We obtain the corresponding travel times from our travel time estimates described in Section 2.4 and convert these into travel costs $\tau(d)$, assuming that

16. We update the guess by calculating the searchers' expectation via the expression

$$\tilde{W} = \frac{1}{l} \sum_{d^{\Delta} \in \mathscr{D}^{\Delta}} \gamma(p(d^{\Delta}))\Big(V_m(d^{\Delta}, E[\varepsilon|_{\varepsilon \geq \varepsilon^*(d^{\Delta})}]) - p(d^{\Delta})\Big) + (1 - \gamma(p(d^{\Delta})))\Big(\beta W\Big).$$

This alternative expression uses the fact that a buyer purchases an apartment with the probability of sale and continues to search with one minus the probability of sale. See Krainer and LeRoy (2002) for details on this approach.

$\tau(d) = \mu \cdot \tilde{\tau}(d)$, where $\tilde{\tau}(d)$ is the travel time that we obtain from the data. μ reflects the cost (in model units) of traveling two minutes by car, as agents commute back and forth between their apartment and the city center each day. $\tilde{\tau}(d)$ measures the travel time to the city center in minutes at some distance to the city center d. We calibrate the model for each city separately and fix the discount factor β across cities.

Table 3.2. Externally calibrated parameters

Parameter	Description	Value	Source
β	Discount factor	0.99986 (yearly: 0.95)	Standard parameter
π^{Hamburg}	Housing match persistence	0.99971 (yearly: 0.90)	Apartment holding periods
π^{Cologne}	——— " ———	0.99970 (yearly: 0.89)	——— " ———
$\pi^{\text{Frankfurt}}$	——— " ———	0.99971 (yearly: 0.90)	——— " ———
$\pi^{\text{Duesseldorf}}$	——— " ———	0.99972 (yearly: 0.90)	——— " ———

Externally calibrated parameters. We set $\beta = \sqrt[365]{0.95} \approx 0.99986$, such that the annual discount factor is 0.95. The housing match persistence for Cologne is given by $\pi^{\text{Cologne}} = 1 - \frac{1}{109.5 \cdot 30} \approx 0.99970$, as the average holding period for apartments in the data is 109.5 months. This value refers to observations from January 1990 to December 2022. We increase the time span for the calibration of this parameter to capture the full length of holding periods, which typically span about nine years, as well as possible.[17] The housing match persistence for Duesseldorf is $\pi^{\text{Duesseldorf}} = 1 - \frac{1}{120.7 \cdot 30} \approx 0.99972$. For Hamburg and Frankfurt we do not have data on holding periods available, hence we use the average holding period across all other cities. On a yearly basis, the probability of being unmatched is about 10% in every city. You can find an overview of the externally calibrated parameters in Table 3.2.

Table 3.3. Internally calibrated parameters

Parameter	Description	Value	Target	Target (model) value
μ^{Hamburg}	Time-to-money conv.	0.00274	Daily car operating costs	14.17 (14.17) €
μ^{Cologne}	——— " ———	0.00903	——— " ———	14.17 (14.16) €
$\mu^{\text{Frankfurt}}$	——— " ———	0.00396	——— " ———	14.17 (14.18) €
$\mu^{\text{Duesseldorf}}$	——— " ———	0.00759	——— " ———	14.17 (14.19) €
$\tilde{\varepsilon}^{\text{Hamburg}}$	Idiosyncratic dist. bound.	0.4499	Avg. time on the market	14.38 (14.38) weeks
$\tilde{\varepsilon}^{\text{Cologne}}$	——— " ———	0.6203	——— " ———	12.12 (12.12) weeks
$\tilde{\varepsilon}^{\text{Frankfurt}}$	——— " ———	0.3962	——— " ———	15.98 (15.98) weeks
$\tilde{\varepsilon}^{\text{Duesseldorf}}$	——— " ———	0.5363	——— " ———	13.33 (13.33) weeks

17. The housing match persistence exhibits very little variation across space when we take into account the spatial variation in holding periods (see Figure 3.F.5 in the Appendix for the spatial distribution of π^{Cologne} as an example), so we calibrate it using the average holding period.

Internally calibrated parameters. With the travel cost function parameter μ we target average daily car operating costs in Germany of 14.17€ (Andor et al., 2020)[18], since our travel time data refer to car travel times. We convert between model units and Euros via the average apartment sales price in a city, hence, we match the average price automatically.

With the housing dividend distribution parameter $\tilde{\varepsilon}$ we target the city-specific average time on the market in the data. Intuitively, we allow differences in buyer preferences between cities to account for differences in the average time on the market between cities. When calibrating this parameter, we reposition the uniform distribution until the values that buyers can draw imply search times that match the average time on the market from the data. You can find an overview of the internally calibrated parameters in Table 3.3.

18. See: supplementary information, Table 3, total monthly car operating costs.

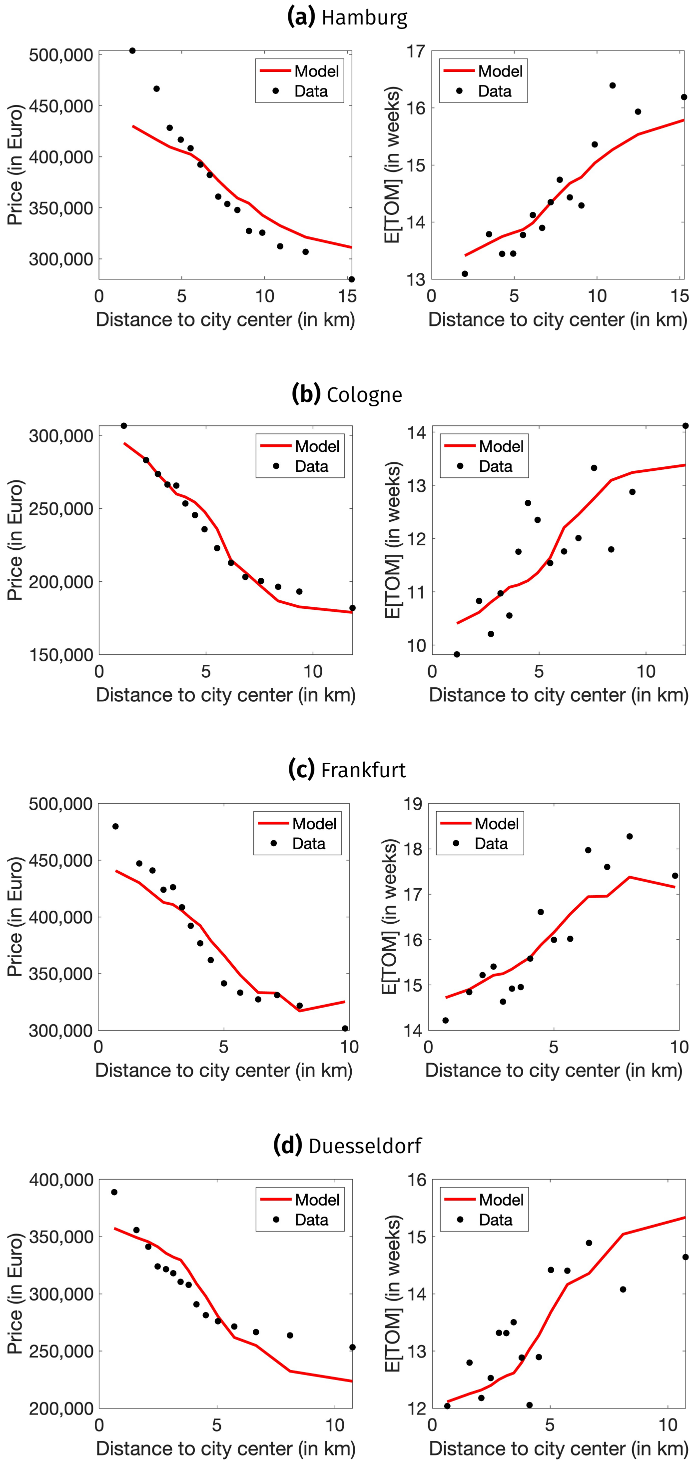

Figure 3.9. Model results: spatial distributions of prices and liquidity

Note: “TOM” refers to time on the market. The data are calculated using the regression specification (3.2) with year-quarter fixed effects and apartment characteristics controls.

3.4.6 Model results

Even though we do not target the spatial gradient of any of our two main variables, price and expected time on the market, our results exhibit spatial variation that closely aligns with the data. We plot a comparison of data and model values in Figure 3.A.1. For each city, we display the average apartment sales price and time on the market by distance to the city center from the data, controlling for apartment characteristics and time fixed effects, together with our model results. Our model matches the spatial price and liquidity gradients with high precision precision in all cities. Figures 3.F.1 to 3.F.4 in the Appendix show the model results for other endogenous variables.

3.5 Housing liquidity and asset pricing

In the previous sections, we presented empirical evidence and a theoretical framework showing that apartment prices and liquidity decrease with distance to the city center. Liquidity differences may partly explain the price differences between city center and outskirts, implying that buyers are willing to pay a liquidity premium to own an apartment in the city center. In this section, we measure this liquidity premium and examine how it changes with distance to the city center.

We think of apartment prices being composed of a fundamental value and a liquidity premium. We want to measure the liquidity premium by distance to the city center to quantify how much liquidity matters for the pricing of apartments across space. Both the fundamental value and the liquidity premium depend on the distance to the city center, which makes it challenging to disentangle these two variables empirically.[19]

Hence, we use our model to structurally estimate the liquidity premium. Following Krainer and LeRoy (2002), we remove search frictions from our model[20] and compare the resulting price gradient to the price gradient from the equilibrium with search frictions.[21] In our model, search frictions grant sellers local monopoly power, enabling them to set high prices in the city center while selling with a low time on the market.

Efficient allocation. To obtain the efficient allocation, we maximize the discounted average net utility of matched and unmatched agents. Recall that agents

19. Measuring the liquidity premium in other asset classes is more straightforward given that the assets' cash flow and maturity are directly observable (e.g. Amihud and Mendelson, 1986). In housing markets, however, the cash flow is typically a latent variable, which needs to be estimated.

20. Intuitively, an efficient version of the market in our model can be best approximated by a market with a very thick seller side. Buyers in such a market have many outside options, which eliminates the price setting power of sellers.

21. The price gradient from our model with search frictions corresponds to the price gradient in the data as shown in section 3.4.

have linear utility functions and unmatched agents live in rental housing in the city center, receiving zero net utility. Hence, we equivalently maximize the sum of housing dividends, that is, the housing utility of matched agents, net of travel costs. Assuming a steady state, we choose reservation dividends $\varepsilon^{\text{eff}}(d^{\Delta})$ in the discretized model to maximize welfare

$$\mathbb{W} = \sum_{t=0}^{\infty} \beta^t \left(\frac{1}{l} \sum_{d^{\Delta} \in \mathscr{D}^{\Delta}} \left(m(d^{\Delta})(E[\bar{\varepsilon}(d^{\Delta})] - \bar{\tau}(d^{\Delta})) \right) \right), \tag{3.24}$$

where $m(\cdot)$ denotes the unconditional probability of being matched and bars denote average values at a given distance to the city center. Due to the uniform distribution of idiosyncratic dividends, agents at distance d^{Δ} have an average dividend of $\frac{\varepsilon^{\text{eff}}(d^{\Delta})+\tilde{\varepsilon}}{2}$. All agents at distance d^{Δ} pay travel costs $\tau(d^{\Delta})$. As there are no further constraints, we equivalently maximize

$$m(d^{\Delta}) \left(\frac{\varepsilon^{\text{eff}}(d^{\Delta}) + \tilde{\varepsilon}}{2} - \tau(d^{\Delta}) \right) \tag{3.25}$$

at every distance $d^{\Delta} \in \mathscr{D}^{\Delta}$. Next, we calculate the probability of being matched $m(d^{\Delta})$. The transition matrix for the states “matched” (up, left) and “unmatched” (down, right) is

$$\mathbb{T} = \begin{pmatrix} \pi & 1 - \pi \\ \pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta})) & 1 - \pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta})) \end{pmatrix}, \tag{3.26}$$

where agents transition from being unmatched to being matched with probability $1 - F(\varepsilon^{\text{eff}}(d^{\Delta})) = \tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta})$ and keep the apartment with probability π. The steady-state probability of being matched is $m(d^{\Delta}) = \pi m(d^{\Delta}) + \pi(\tilde{\varepsilon} - \varepsilon^{sp}(d^{\Delta}))(1 - m(d^{\Delta}))$, and thus

$$m(d^{\Delta}) = \frac{\pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))}{1 - \pi + \pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))}. \tag{3.27}$$

The optimal reservation dividend at distance d^{Δ} is hence given by

$$\underset{\varepsilon^{\text{eff}}(d^{\Delta})}{\operatorname{argmax}} \left(\frac{\pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))}{1 - \pi + \pi(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))} \right) \left(\frac{\varepsilon^{\text{eff}}(d^{\Delta}) + \tilde{\varepsilon}}{2} - \tau(d^{\Delta}) \right), \tag{3.28}$$

which we calculate numerically. We get the associated price via (3.15):

$$p^{\text{eff}}(d^{\Delta}) = \frac{\beta}{1 - \pi\beta}(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta})) + \frac{\beta^2}{(1 - \beta)(1 - \pi\beta)}(\tilde{\varepsilon} - \varepsilon^{\text{eff}}(d^{\Delta}))^2. \tag{3.29}$$

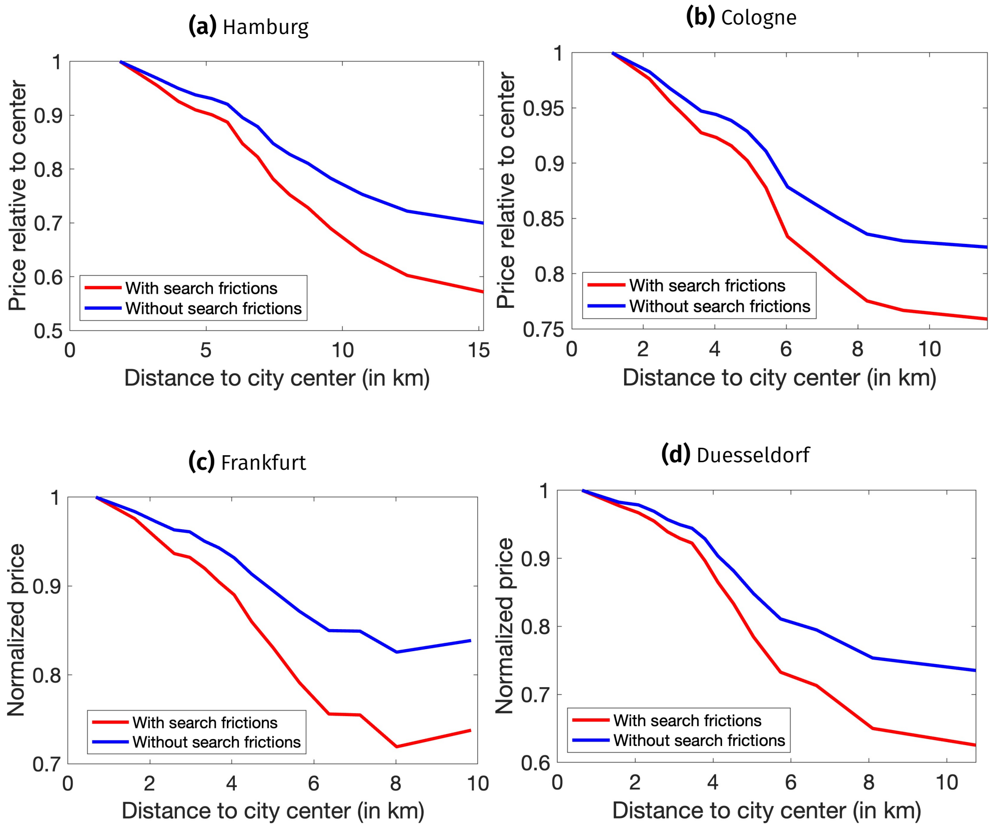

Figure 3.10. Normalized spatial price gradients, with and without search frictions

Note: The plot shows the equilibrium prices from our calibrated model ("with search frictions"), the prices from the efficient allocation ("without search frictions") as specified in (3.29), and the .

Liquidity premium. Next, to evaluate the liquidity premium in the city center (distance d_1^Δ) relative to some distance d^Δ, we compare the relative prices by distance to the city center from the efficient allocation $p^{\text{eff}}(d^\Delta)/p^{\text{eff}}(d_1^\Delta)$ to the relative prices from the frictional allocation $p(d^\Delta)/p(d_1^\Delta)$ and plot the resulting relative price gradients in Figure 3.10. We define the liquidity premium in the city center relative to distance d^Δ as

$$l(d^\Delta) = p^{\text{eff}}(d^\Delta)/p^{\text{eff}}(d_1^\Delta) - p(d^\Delta)/p(d_1^\Delta). \tag{3.30}$$

We interpret this difference as the cost of illiquidity at distance d^Δ relative to the city center. Note that in the efficient allocation, liquidity is not infinite, in other words, the expected time on the market is not equal to zero. Agents have a benefit from searching until they have found an apartment for which they draw a high enough reservation dividend.[22] We plot the resulting liquidity premium curves in

22. Depending on the calibration, there can be too little or too much search implied by the frictional allocation compared to the efficient allocation (see Krainer and LeRoy (2002)). With our cali-

Figure 3.11. Our model implies liquidity premiums in the city center relative to the outskirts of about 6% to 12% of the house price in the city center. The average spatial liquidity premium at 10 km across cities and discount factors is 8%.

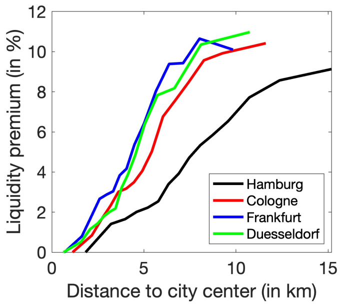

Figure 3.11. Liquidity premium across space

Note: The plot shows the liquidity premium in the city center relative to a given distance to the city center, as defined in (3.30), in terms of the house price in the city center.

Sensitivity analysis. In the calibration of our model, we set the yearly discount factor to 0.95. The other parameters are either directly obtained from our transaction data or internally calibrated. We check to what extent the liquidity premium changes if we use a different discount factor. More patient agents should be less interested in the time on the market of apartments, as the cost of liquidity materializes in the short term. In Figure 3.10, we plot the liquidity premium at a distance to the city center of 10km for all cities, varying the discount factor between 0.93 and 0.97. If we increase the discount factor, the liquidity premium becomes smaller in most cases, however, only in a small order of magnitude. We attribute the small increases in the liquidity premium for some discount factors to the non-linearity of the model and the travel time inputs, which make the behavior of prices in the city center relative to those in the outskirts behave non-linearly in response to changes in parameters. On average, across cities and discount factors, we observe a liquidity premium at 10km distance to the city center of about 8% of the house price in the city center.

Search frictions and data fit. Using the results on the spatial price gradients with and without search frictions and our spatial price gradients from the data (see Figure 3.5), we can compare if and to what extent search frictions in the model improve the fit to the price data. From Figure 3.10, we observe that the model with search frictions fits the price gradients from the data better than the model without search frictions. The data points in the plot are normalized such that the average price in

bration, we are in a region of parameter combinations with which agents search too much in every city. Hence, the expected time on the market implied by the efficient allocation is lower than the expected time on the market implied by the frictional allocation.

the data aligns with the average price from the model with search frictions, as in our calibration. To quantify the improvement in the fit to the data, we regress log prices from the two model versions and from the data on the distances to the city center, as done for Figure 3.5. Then, we calculate the difference in the coefficients for the distance to the city center between the version with and without search frictions, relative to the coefficient from the regressions using the data. The resulting measure captures the quantitative role of spatial liquidity differences due to search frictions in explaining the spatial price gradient from the data. For Hamburg, search frictions explain 21% of the spatial price gradient, and for Cologne, Frankfurt, and Duesseldorf, they explain 34%, 33%, and 42% of the spatial price gradient. On average across cities, this amounts to 32%, and we conclude that spatial liquidity differences due to search frictions explain about a third within-city spatial price gradient.

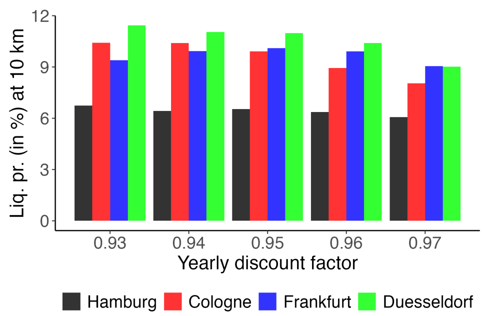

Figure 3.12. Liquidity premium at 10km distance to the city center

Note: The plot shows the liquidity premium in the city center compared to a distance of 10km to the city center, as defined in (3.30), in terms of the house price in the city center, for different yearly discount factors. The yearly discount factor in the main model is 0.95.

3.6 Summary and concluding remarks

In this paper, we demonstrate that housing market liquidity decreases with distance to the city center, using a novel data set with matched apartment transactions and advertisements from large German cities between January 2012 and December 2022. We rationalize our findings in a spatial search model of a housing market in a monocentric city. We show analytically that as an inherent characteristic of the model, the expected time on the market decreases with distance to the city center jointly with the sales price. We calibrate the model with our data set and obtain a quantitatively precise fit to the data. Using our model, we estimate a liquidity premium in the city center compared to the outskirts of 8% of the apartment price in the city center. We conclude that liquidity is priced in a large magnitude across space in urban housing markets.

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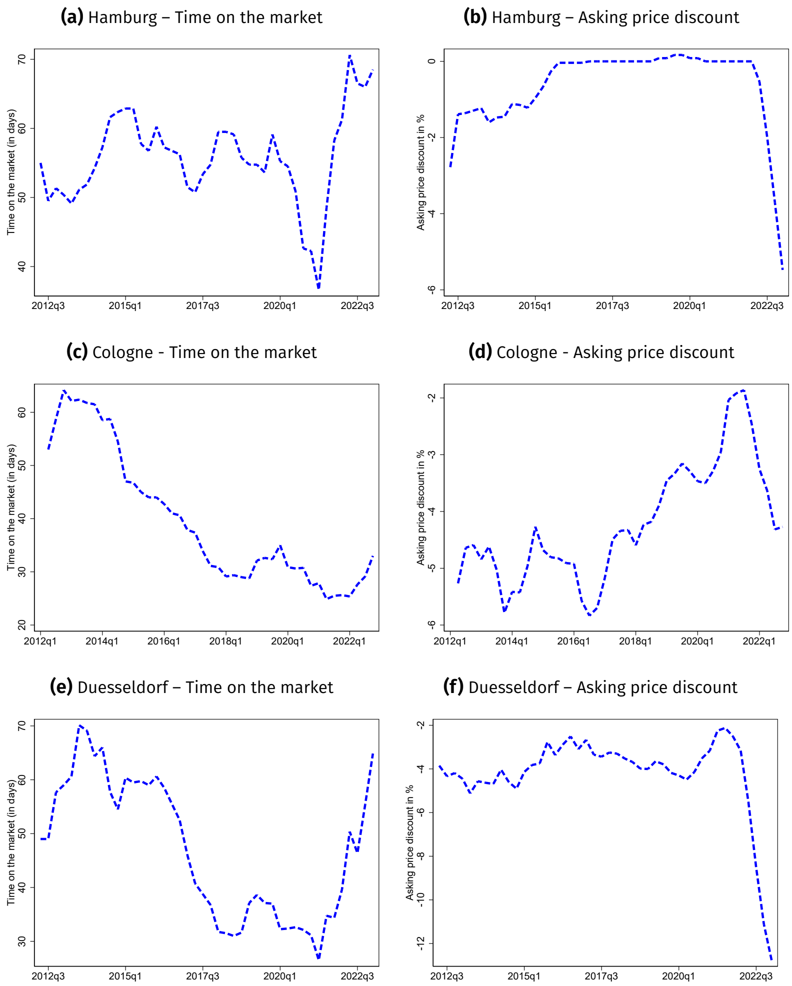
Appendix 3.A Additional empirical results

In this section of the appendix, we provide figures and tables that support the empirical findings in this paper. We begin by presenting the regression output tables, which analyze the relation between time on the market and distance to the city center. We display one table per city. Following this, we present additional empirical results and visualizations regarding the spatial distribution of transaction prices and asking prices.

3.A.1 Time series of housing liquidity



(a) Hamburg – Time on the market

(b) Hamburg – Asking price discount

(c) Cologne - Time on the market

(d) Cologne - Asking price discount

(e) Duesseldorf – Time on the market

(f) Duesseldorf – Asking price discount

Figure 3.A.1. Time series of liquidity

3.A.2 Additional determinants of housing market liquidity

In our main analysis, we exclusively focus on how liquidity affects prices via the location of the house. Nevertheless, houses differ in other dimensions which might also impact their liquidity. In particular, the size and age of the property might be strong determinants of liquidity, as typically the market is also segmented along these dimensions. In other words, the market for larger houses might be thinner than that for smaller houses. Although our focus in this paper is not on these additional dimensions, we also provide evidence that location has a stronger effect on liquidity than these other factors. In Figure 3.A.2, we plot the standardized coefficients for size as measured by living area square meters, age of the building, and distance to the city center. The coefficients are derived from regression 3.2. As we can see, all coefficients are positive and significant, suggesting that these dimensions have a significant impact on liquidity as measured by time on the market. Nevertheless, as is also evident from the graph, distance to the city center has the largest impact on liquidity.

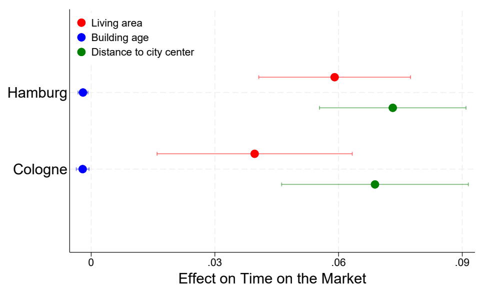


Figure 3.A.2. Determinants of time on the market, (January 2012- December 2022)

Note: These figures show the OLS regression coefficients by city, as well as its respective 99% confidence intervals. See Footnote 6 for a full list of these characteristics. Distance to the city center is measured as the kilometer distance. The coefficients are standardized and thus comparable.

3.A.3 Time on the market – regression output tables

Table 3.A.1. Relation between time on the market and distance to the city center (Cologne, January 2012- December 2022)

	TOM	TOM	TOM	TOM
Distance to center (in km)	0.32^{***}	0.29^{***}		
	(0.09)	(0.07)		
Travel time to center (in min)			0.16^{***}	0.13^{***}
			(0.04)	(0.03)
Quarter FEs	Yes	Yes	Yes	Yes
Property Characteristics	No	Yes	No	Yes
N	14188	14188	14188	14188
R^2	0.08	0.13	0.08	0.13

Note: This table shows results for regressions of the time on the market on the distance to the city center as specified in the regression specification (3.2). "TOM" refers to the time on the market in weeks as defined in (3.1). Standard errors (in parentheses) are clustered at the borough (*Stadtbezirk*) level. The property characteristics are control variables. See Footnote 6 for a full list of these characteristics.
$* : p < 0.1; ** : p < 0.05; *** : p < 0.01.$

Table 3.A.2. Relation between time on the market and distance to the city center (Hamburg, January 2012- December 2022)

	TOM	TOM	TOM	TOM
Distance to center (in km)	0.37^{***}	0.26^{***}		
	(0.03)	(0.05)		
Travel time to center (in min)			0.16^{***}	0.11^{***}
			(0.01)	(0.01)
Quarter FEs	Yes	Yes	Yes	Yes
Property Characteristics	No	Yes	No	Yes
N	20672	20672	20672	20672
R^2	0.02	0.11	0.02	0.11

Note: This table shows results for regressions of the time on the market on the distance to the city center as specified in the regression specification (3.2). "TOM" refers to the time on the market in weeks as defined in (3.1). Standard errors (in parentheses) are clustered at the borough (*Stadtbezirk*) level. The property characteristics are control variables. See Footnote 6 for a full list of these characteristics.
$* : p < 0.1; ** : p < 0.05; *** : p < 0.01.$

3.A.4 Spatial distributions of transaction and asking prices

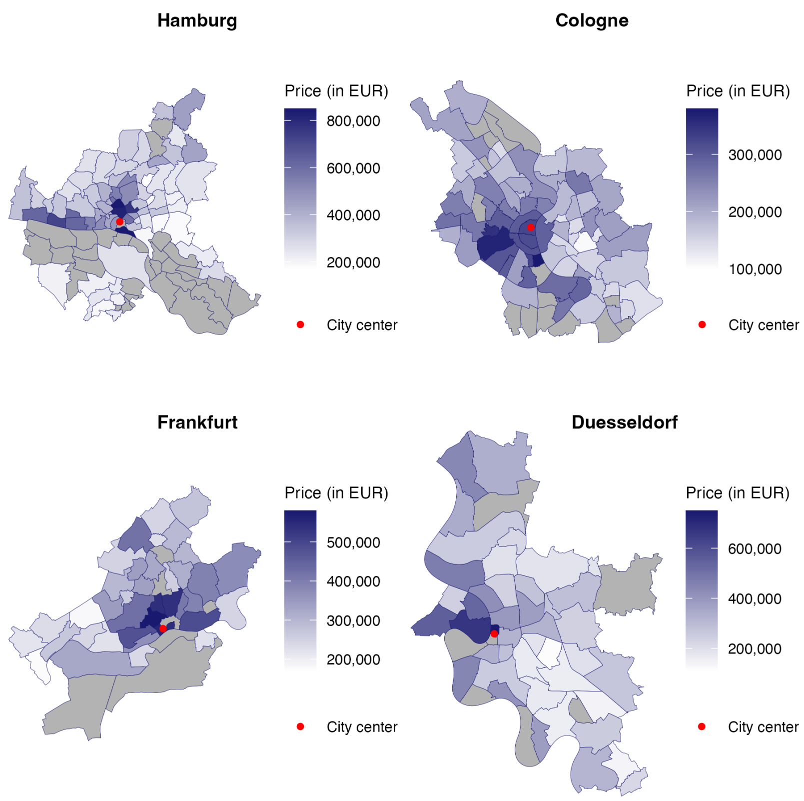


Figure 3.A.3. Transaction prices across space (January 2012- December 2022)

Note: The maps show the average transaction price by district (*Stadtteil*) from our matched data set, controlling for year-quarter fixed effects. Districts without available data are colored gray.

(a) Hamburg

(b) Cologne

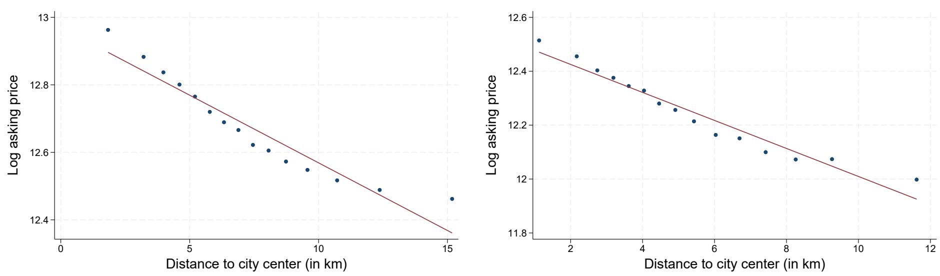


Figure 3.A.4. Spatial gradients of asking prices (January 2012- December 2022)

Note: These binscatter plots visualize the results of the regression specification (3.2) with log asking price as the outcome variable and 15 equally-sized distance bins. The city center is the Cologne Cathedral. The regressions control for year-quarter fixed effects and apartment characteristics. See Footnote 6 for a full list of these characteristics.

Appendix 3.B Robustness analysis

In this section of the Appendix, we offer additional empirical evidence supporting the robustness analysis section of the paper. Before delving into the empirical analysis, we present histograms with the distribution of asking price discounts by city. We then present evidence showing that the asking price discount becomes increasingly negative with distance from the city center. Here, we provide both binscatters and regression output tables. Next, we demonstrate that our baseline results remain robust across different regression specifications. We present the regression output tables for the alternative specifications outlined in Section 3.3 of the paper, with one table per city.

3.B.1 Asking price discount

In Figure 3.B.1, we plot a histogram of the asking price discount for our matched sample by city. The majority of transactions exhibit a negative discount, that is, properties typically sell below their asking prices. The distribution resembles a normal distribution but has a more positive skew and thinner tails. On average, a property is transacted at a sales price below its asking price. There is a clear bunching at an asking price discount of 0%. This finding has been documented for other countries as well and reflects that the asking price is a relevant anchor for the bargaining process in housing markets, as it is a partial commitment for the seller (Han and Strange, 2016).

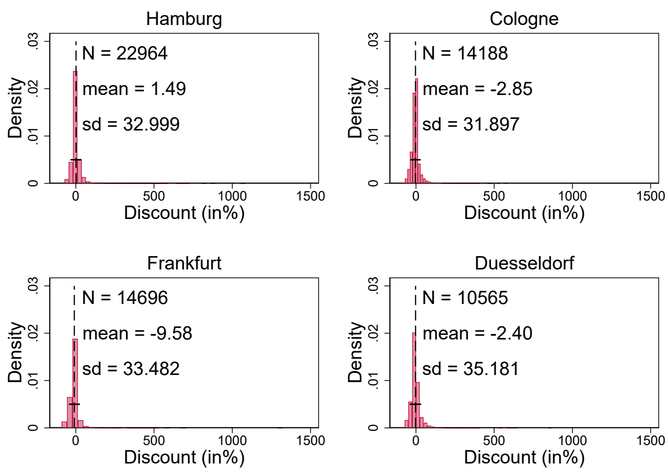


Figure 3.B.1. Histograms of asking price discount (January 2012- December 2022)

Note: This figure shows histograms for the asking price discount in our matched data set, where we calculate this measure of liquidity as defined in (3.3).

Table 3.B.1. Relation between asking price discount and distance the to city center (Cologne, January 2012- December 2022)

	Discount	Discount	Discount	Discount
Distance to center (in km)	-0.61**	-0.41		
	(0.19)	(0.23)		
Travel time to center (in min)			-0.29**	-0.18
			(0.10)	(0.13)
Quarter FEs	Yes	Yes	Yes	Yes
Property Characteristics	No	Yes	No	Yes
N	14188	14188	14188	14188
R^2	0.01	0.07	0.01	0.07

Note: This table shows results for regressions of the asking price discount on the distance to the city center as specified in the regression specification (3.2). "Discount" refers to the asking price discount in percent as defined in (3.3). Standard errors (in parentheses) are clustered at the borough (*Stadtbezirk*) level. The property characteristics are control variables. See Footnote 6 for a full list of these characteristics.
$* : p < 0.1; ** : p < 0.05; *** : p < 0.01.$

Table 3.B.2. Relation between asking price discount and distance the to city center (Hamburg, January 2012- December 2022)

	Discount	Discount	Discount	Discount
Distance to center (in km)	-0.40**	-0.39**		
	(0.15)	(0.13)		
Travel time to center (in min)			-0.30***	-0.32***
			(0.06)	(0.05)
Quarter FEs	Yes	Yes	Yes	Yes
Property Characteristics	No	Yes	No	Yes
N	22963	22963	22963	22963
R^2	0.01	0.06	0.02	0.06

Note: This table shows results for regressions of the asking price discount on the distance to the city center as specified in the regression specification (3.2). "Discount" refers to the asking price discount in percent as defined in (3.3). Standard errors (in parentheses) are clustered at the borough (*Stadtbezirk*) level. The property characteristics are control variables. See Footnote 6 for a full list of these characteristics.
$* : p < 0.1; ** : p < 0.05; *** : p < 0.01.$

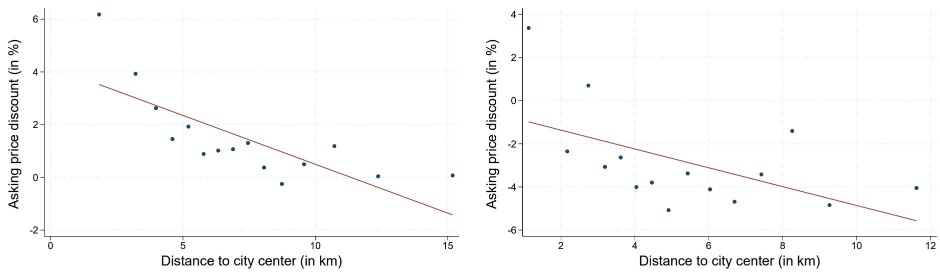


Figure 3.B.2. Spatial gradients of asking price discount (January 2012- December 2022)

Note: These binscatter plots visualize the results of regression (3.2) with log asking price as the outcome variable and 15 equally-sized distance bins. The regressions include year-quarter fixed effects and control for apartment characteristics listed in Footnote 6.

3.B.2 Alternative regression specifications

In this section of the Appendix, we present the regression output tables for the alternative specifications as described in Section 3.3 of the paper. Table 3.B.3 presents the results for Cologne. Table 3.B.4 presents the results for Hamburg.

Table 3.B.3. Alternative specifications (Cologne, January 2012- December 2022)

	Poisson	Poisson	Log TOM	Log TOM
Distance to center (in km)	0.03***	0.03***	0.04***	0.04***
	(0.00)	(0.01)	(0.01)	(0.01)
Quarter FEs	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	13076	13076	13076	13076

Note: This table shows results for regressions of the time on the market on the euclidian distance to the city center. The first two columns show the results for the Poisson regressions. The last two columns shows the results for the regression specification where we use log time on the market as dependent variable. Here we follow the specification of regression (3.2). Standard errors (in parentheses) are clustered at the borough (*Stadtbezirk*) level. The property characteristics are control variables. See Footnote 6 for a full list of these characteristics.
$*: p < 0.1; **: p < 0.05; ***: p < 0.01.$

Table 3.B.4. Alternative specifications (Hamburg, January 2012- December 2022)

	Poisson	Poisson	Log TOM	Log TOM
Distance to center (in km)	0.03***	0.02***	0.04***	0.02***
	(0.00)	(0.00)	(0.01)	(0.00)
Quarter FEs	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	20672	20672	20672	20672

Note: This table shows results for regressions of the time on the market on the euclidian distance to the city center. The first two columns show the results for the Poisson regressions. The last two columns shows the results for the regression specification where we use log time on the market as dependent variable. Here we follow the specification of regression (3.2). Standard errors (in parentheses) are clustered at the borough (*Stadtbezirk*) level. The property characteristics are control variables. See Footnote 6 for a full list of these characteristics.
$* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

Appendix 3.C Second-order condition of the seller's problem

The first-order condition of the seller's profit maximization problem is

$$\frac{\partial \Pi}{\partial p} = \gamma(p(d)) + p(d)\frac{\partial \gamma}{\partial p}\bigg|_{p=p(d)} - \beta \Pi(d)\frac{\partial \gamma}{\partial p}\bigg|_{p=p(d)} = 0. \tag{3.C.1}$$

Hence, the second-order condition for a maximum is

$$\frac{\partial^2 \Pi}{\partial p^2} = 2\frac{\partial \gamma}{\partial p}\bigg|_{p=p(d)} + \frac{\partial^2 \gamma}{\partial p^2}\bigg|_{p=p(d)}(p(d) - \beta \Pi(d)) < 0. \tag{3.C.2}$$

Using (3.13), we know that

$$\frac{\partial \gamma}{\partial p}\bigg|_{p=p(d)} = -\frac{1-\pi\beta}{\beta} < 0. \tag{3.C.3}$$

Therefore,

$$\frac{\partial^2 \gamma}{\partial p^2}\bigg|_{p=p(d)} = 0, \tag{3.C.4}$$

and

$$\frac{\partial^2 \Pi}{\partial p^2} = -2\,\frac{1-\pi\beta}{\beta} < 0, \tag{3.C.5}$$

which provides the required maximum.

Appendix 3.D Extended model with bargaining

We extend our model by a bargaining process, following Carrillo (2012). With this addition, our model features an asking price and a sales price, which allows us to form a notion of a second measure of liquidity in the model. The asking price discount (APD) measures the relative difference between asking and sales prices, as in the supplementary empirical results. In the model, the asking price discount is always negative, that is, apartments always sell below their asking prices.

The search process in the extended model features the following changes. When a buyer visits an apartment, the buyer and the seller may or may not bargain, which is determined stochastically. With probability θ, the seller does not accept counteroffers, and $p(d)$ is a take-it-or-leave-it offer ("no-counteroffer scenario", subscript n). The buyer accepts or rejects the offer. If the buyer accepts, the seller receives $p(d)$, and the buyer receives their first housing dividend ε in the following period and pays their first commuting costs $\tau(d)$ in the following period. If the buyer rejects, the seller relists the apartment in the following period and the buyer visits a new apartment in the following period. With probability $(1-\theta)$, the buyer can bargain by making a take-it-or-leave-it counteroffer $o(d)$ to the seller ("counteroffer scenario", subscript c). If the buyer makes a counteroffer, the seller accepts or rejects the offer. The outcomes of accepting or rejecting the offer are analogous to those in the no-counteroffer scenario.

Changes in the seller problem. The seller maximizes their profits $\Pi(d)$ over an asking price $p(d)$ and a reservation value $r(d)$. We assume that a buyer has perfect information about a seller's preferences (Carrillo (see 2012)). Hence, in the counteroffer scenario, the offer $o(d)$ is equal to the seller's reservation value $r(d)$, as this offer corresponds to the lowest price the seller is willing to accept. In the following, we denote by $\gamma_n(p(d))$ the probability that a buyer is willing to buy in the no-counteroffer scenario and the seller posts an asking price $p(d)$. The respective probability in the counteroffer scenario is $\gamma_c(p(d))$. Profits are given by

$$\begin{aligned} \Pi(d) \;=\; \max_{p(d),r(d)} & \Big\{\theta\Big(\gamma_n(\cdot)p(d) + (1-\gamma_n(\cdot))\beta\Pi(d)\Big) \\ & + (1-\theta)\Big(\gamma_c(\cdot)\max[r(d),\beta\Pi(d)] + (1-\gamma_c(\cdot))\beta\Pi(d)\Big)\Big\}. \end{aligned} \tag{3.D.1}$$

In the no-counteroffer scenario, which happens with probability θ, the seller receives the price $p(d)$ with probability $\gamma_n(\cdot)$ and receives discounted continuation value $\beta\Pi(d)$ of trying to sell the house again next period with probability $(1-\gamma_n(\cdot))$. In the counteroffer scenario, which happens with probability $(1-\theta)$, the seller receives the maximum of the counteroffer $o(d) = r(d)$ and the discounted continuation value $\beta\Pi(d)$, depending on whether they accept or reject the buyer's counteroffer, with probability $\gamma_c(\cdot)$. The seller receives the discounted continuation value of $\beta\Pi(d)$ with probability $(1-\gamma_c(\cdot))$ analogously to the counteroffer scenario.

Changes in the buyer problem. The buyer's search value is given by:

$$W \;=\; E_{x,\varepsilon}\left[\theta V_n(d,\varepsilon) + (1-\theta)V_c(d,\varepsilon)\right], \tag{3.D.2}$$

With probability θ, the buyer receives the buyer's value in the no-counteroffer scenario $V_n(d,\varepsilon)$. With probability $(1-\theta)$, the buyer receives the buyer's value in the counteroffer scenario $V_c(d,\varepsilon)$. The buyer's value in the no-counteroffer scenario is

$$V_n(d,\varepsilon) \;=\; \max[V_m(d,\varepsilon) - p(x), \beta W]. \tag{3.D.3}$$

Either the buyer accepts the asking price and receives the continuation value of being matched $V_m(d,\varepsilon)$, which we denote by $V(d,\varepsilon)$ in the main model, while paying $p(d)$, or the buyer continues to search and receives the discounted value of searching next period, βW. The buyer's value in the counteroffer scenario is

$$V_c(d,\varepsilon) \;=\; \max[\delta(\cdot)(V_m(d,\varepsilon)-o(d))+(1-\delta(\cdot))(\beta W),\beta W], \tag{3.D.4}$$

where $\delta(o(d))$ denotes the probability that the seller accepts the buyer's counteroffer. If the seller accepts, the buyer receives the continuation value of being matched $V_m(d,\varepsilon)$ while paying the counteroffer price $o(d)$. If the seller rejects the counteroffer, the buyer keeps on searching and receives the discounted value of search. The buyer can also decide not to make a counteroffer and keep on searching by themselves. Note that the seller always accepts the optimal counteroffer $o(d)=r(d)$. Hence, $\delta(\cdot)=1$ at all distances to the city center.

3.D.1 Equilibrium in the extended model

Seller's optimization. Since the counteroffer $o(d)=r(d)$ is the lowest price that the seller is willing to accept, the seller's reservation value is given by $r(d)=\beta\Pi(d)$. With any reservation value above $\beta\Pi(d)$, it would be better for the seller to reject the buyer's offer and relist the apartment next period. The expression for seller profits (3.D.1) then simplifies to

$$\Pi(d) \;=\; \max_{p(d),r(d)}\Big\{\theta\gamma_n(\cdot)p(d)+(1-\theta\gamma_n(\cdot))r(d)\Big\}. \tag{3.D.5}$$

Optimizing with regards to the asking price $p(d)$ yields

$$p(d) \;=\; r(d)-\frac{\gamma_n(\cdot)}{\partial\gamma_n/\partial p\;|_{p=p(d)}}, \tag{3.D.6}$$

where the derivative $\partial\gamma_n/\partial p$ is evaluated at the optimal asking price $p(d)$. Plugging the condition $r(d)=\beta\Pi(d)$ into (3.D.5) evaluated at the seller's optimum, we have that

$$\begin{aligned}\frac{r(d)}{\beta} \;&=\; \theta\gamma_n(\cdot)p(d)+(1-\theta\gamma_n(\cdot))r(d)\\ \Rightarrow r(d) \;&=\; \frac{\beta\theta\gamma_n(\cdot)p(d)}{1-\beta\left(1-\theta\gamma_n(\cdot)\right)}.\end{aligned} \tag{3.D.7}$$

The pair of the optimal asking price and reservation value for a given distance to the city center solves the previous equations (3.D.6) and (3.D.7) simultaneously.

Buyer's optimization. Via the buyer value function in the no-counteroffer scenario (3.D.3), we define a reservation dividend $\varepsilon_n^*(d)$ such that a buyer is indifferent indifferent between buying an apartment and continuing to search:

$$V_m(d, \varepsilon_n^*(d)) - p(d) \;=\; \beta W. \tag{3.D.8}$$

Analogously, via the buyer value function in the counteroffer scenario (3.D.4), we define a reservation dividend $\varepsilon_c^*(d)$ such that

$$V_m(d, \varepsilon_c^*(d)) - r(d) \;=\; \beta W. \tag{3.D.9}$$

Probability of sale. The probability of sale conditional on a bargaining scenario is equal to the probability that the buyer's idiosyncratic dividend is above their respective reservation dividend. Hence, in the no-counteroffer scenario,

$$\begin{aligned}\gamma_n(p(d)) \;&=\; Prob(\varepsilon \;>\; \varepsilon_n^*(d)) \;=\; 1 - Prob(\varepsilon \;\leq\; \varepsilon_n^*(d)) \\ &=\; \tilde{\varepsilon} - \varepsilon_n^*(d).\end{aligned} \tag{3.D.10}$$

Analogously, in the counteroffer scenario,

$$\gamma_c(p(d)) \;=\; \tilde{\varepsilon} - \varepsilon_c^*(d). \tag{3.D.11}$$

Thus, for the derivative in the seller optimality condition (3.D.6) we have that

$$\left.\frac{\partial \gamma_n}{\partial p}\right|_{p=p(d)} \;=\; -\left.\frac{\partial \varepsilon_n^*}{\partial p}\right|_{p=p(d)} \tag{3.D.12}$$

for all distances to the city center $d \in \mathcal{D}$. By proceeding as in the main derivations, we get

$$\varepsilon_n^*(d) \;=\; \frac{1-\pi\beta}{\beta} p(d) + \tau(d) - (1-\pi)\Pi(d) + (\pi - \pi\beta)W \tag{3.D.13}$$

and

$$\left.\frac{\partial \gamma_n}{\partial p}\right|_{p=p(d)} \;=\; -\frac{1-\pi\beta}{\beta}. \tag{3.D.14}$$

Analogous relations hold for the counteroffer scenario.

Equilibrium definition, extended model. A *stationary spatial equilibrium* consists of a seller profit function $\Pi(d)$, an asking price function $p(d)$, a seller reservation value function $r(d)$, a value of search W, buyer reservation dividend functions $\varepsilon_n^*(d)$ and $\varepsilon_c^*(d)$, and conditional sale probability functions $\gamma_n(p(d))$ and $\gamma_c(p(d))$ that satisfy equations (3.D.2), (3.D.5), (3.D.6), (3.D.7), (3.D.8), (3.D.9), (3.D.10), and (3.D.11) for all distances to the city center $d \in \mathscr{D}$, given a parameter vector $(\beta, \pi, \theta, \tilde{\varepsilon})$, a distribution of apartments' distances to the city center $\mathscr{D}$, and a commuting cost function $\tau(d)$.

3.D.2 Analytical results in the extended model

Again, we start with auxiliary derivations. First, Lemma 3.2 allows to simplify expression with reservation dividends and probabilites of sale.

Lemma 3.2. *The buyer reservation dividends in the counteroffer scenario and the no-counteroffer scenario relate as $\varepsilon_c^*(d) = 2\varepsilon_n^*(d) - \tilde{\varepsilon}$. The probabilities of sale in these two scenarios relate as $\gamma_c(p(d)) = 2\gamma_n(p(d))$.*

Proof. Using the buyer indifference condition (3.D.9) and the linear expression of the buyer value function (3.11), we have that

$$\varepsilon_c^*(d) = \frac{1-\pi\beta}{\beta} r(d) + \tau(d) - (1-\pi)(\Pi(d) + W) + (1-\pi\beta)W \tag{3.D.15}$$

$$= \frac{1-\pi\beta}{\beta}\left(p(d) + \frac{\gamma_n(p(d))}{\left.\frac{\partial \gamma_n}{\partial p}\right|_{p=p(d)}}\right) + \tau(d) - (1-\pi)(\Pi(d) + W) + (1-\pi\beta)W \tag{3.D.16}$$

$$= \varepsilon_n^*(d) - \gamma_n(p(d)), \tag{3.D.17}$$

where the last two lines follow due to the seller optimality condition (3.D.6), the linear expression of the reservation value (3.D.13), and the constant value of the derivative $(\partial\gamma_n/\partial p)|_{p=p(d)}$ with a uniformly distributed idiosyncratic dividend (3.D.14). Therefore, we also have that $\varepsilon_c^*(d) = 2\varepsilon_n^*(d) - \tilde{\varepsilon}$, as well as $\gamma_c(p(d)) = 2\gamma_n(p(d))$, via the equilibrium relations between reservation dividends and probabilities of sale (3.D.10) and (3.D.11). □

Lemma 3.3 shows that both of the buyer reservation dividends are increasing with distance to the city center.

Lemma 3.3. *The reservation dividends in the no-counteroffer scenario $\varepsilon_n^*(d)$ and in the counteroffer scenario $\varepsilon_c^*(d)$ increase with distance to the city center x.*

Proof. We know from (3.D.13) that

$$\varepsilon_n^*(d) \;=\; \frac{1-\pi\beta}{\beta}p(d) + \tau(d) - (1-\pi)\Pi(d) + (\pi - \pi\beta)W.$$

Analogously to the main derivations, we reformulate the asking price $p(d)$ and the expected profits from reselling the apartment $\Pi(d)$ in terms of the reservation dividend $\varepsilon_n^*(d)$. First, we combine the seller optimality conditions (3.D.6) and (3.D.7) and get

$$p(d) \;=\; -\frac{(1-\beta)\gamma_n(p(d)) + \beta\theta\gamma_n^2(p(d))}{(1-\beta)\partial\gamma_n/\partial p\;|_{p=p(d)}}. \tag{3.D.18}$$

Expressing the probability of sale $\gamma_n(p(d))$ and the derivative $(\partial\gamma_n/\partial p)\,|_{p=p(d)}$ in terms of the reservation dividend using the equilibrium relations (3.D.10) and (3.D.14), we have that

$$\begin{aligned} p(d) \;&=\; -\frac{(1-\beta)(\tilde{\varepsilon}-\varepsilon_n^*(d)) + \beta\theta(\tilde{\varepsilon}-\varepsilon_n^*(d))^2}{(1-\beta)\left(-\frac{1-\pi\beta}{\beta}\right)} && (3.D.19)\\ &=\; \frac{\beta}{1-\pi\beta}(\tilde{\varepsilon}-\varepsilon_n^*(d)) + \frac{\beta^2\theta}{(1-\beta)(1-\pi\beta)}(\tilde{\varepsilon}-\varepsilon_n^*(d))^2. && (3.D.20)\end{aligned}$$

Next, using the seller's conditions (3.D.5) and (3.D.6), we get

$$\Pi(d) \;=\; p(d) + \frac{\gamma_n(p(d)) - \theta\gamma_n^2(p(d))}{\partial\gamma_n/\partial p\;|_{p=p(d)}}, \tag{3.D.21}$$

which, using (3.D.20) and again expressing the probability of sale and the derivative in terms of the reservation dividend via (3.D.10) and (3.D.14), amounts to

$$\begin{aligned} \Pi(d) \;=&\frac{\beta}{1-\pi\beta}(\tilde{\varepsilon}-\varepsilon_n^*(d)) + \frac{\beta^2\theta}{(1-\beta)(1-\pi\beta)}(\tilde{\varepsilon}-\varepsilon_n^*(d))^2 \\ &- \frac{\beta}{1-\pi\beta}\left((\tilde{\varepsilon}-\varepsilon_n^*(d)) - \theta(\tilde{\varepsilon}-\varepsilon_n^*(d))^2\right) && (3.D.22)\\ =&\frac{\beta\theta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon}-\varepsilon_n^*(d))^2. && (3.D.23)\end{aligned}$$

Therefore, we can express the reservation dividend as

$$\begin{aligned} \varepsilon_n^*(d) \;=\; &\frac{1-\pi\beta}{\beta}\left(\frac{\beta}{1-\pi\beta}(\tilde{\varepsilon}-\varepsilon_n^*(d)) + \frac{\beta^2\theta}{(1-\beta)(1-\pi\beta)}(\tilde{\varepsilon}-\varepsilon_n^*(d))^2\right) \\ &+ \tau(d) - (1-\pi)\left(\frac{\beta\theta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon}-\varepsilon_n^*(d))^2\right) + (\pi-\pi\beta)W. \end{aligned} \tag{3.D.24}$$

After simplifying, we have that

$$2\varepsilon_n^*(d) - 1 + \frac{\pi\beta\theta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon_n^*(d))^2 \;=\; \tau(d) + (\pi - \pi\beta)W. \tag{3.D.25}$$

We take the derivative with respect to the distance to the city center d on both sides and get

$$\frac{\partial \varepsilon_n^*}{\partial d}\underbrace{\left(2 - 2\frac{\pi\beta\theta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon_n^*(d))\right)}_{>0} \;=\; \frac{\partial \tau}{\partial d} \tag{3.D.26}$$

and therefore $\frac{\partial \varepsilon_n^*}{\partial d} > 0$, given that $\frac{\partial \tau}{\partial d} > 0$. Via Lemma 3.2, we have that $\frac{\partial \varepsilon_c^*}{\partial d} = 2\frac{\partial \varepsilon_n^*}{\partial d}$, and hence this relation also applies to the reservation dividend in the counteroffer scenario $\varepsilon_c^*(d)$. □

Via the proof of Lemma 3.3, we directly obtain a description of the spatial variation in other endogenous variables.

Corollary 3.4. *The seller profit $\Pi(d)$, the asking price $p(d)$, the seller reservation value $r(d)$, and the expected sales price $E[\text{Sales price}(d)] = \theta p(d) + (1-\theta)r(d)$ decrease with distance to the city center d.*

Proof. Using (3.D.23), we have that

$$\frac{\partial \Pi}{\partial d} \;=\; \frac{2\beta\theta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d))\left(-\frac{\partial \varepsilon_n^*}{\partial d}\right) \;<\; 0, \tag{3.D.27}$$

where $\frac{\partial \varepsilon_n^*}{\partial d} > 0$ via Lemma 3.3. Next, using (3.D.20), we get

$$\frac{\partial p}{\partial d} \;=\; -\frac{\beta}{1-\pi\beta}\frac{\partial \varepsilon_n^*}{\partial d} + \frac{2\beta^2\theta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d))\left(-\frac{\partial \varepsilon_n^*}{\partial d}\right) \;<\; 0. \tag{3.D.28}$$

We express the seller reservation value in terms of the reservation dividend via (3.D.20), the seller optimality condition (3.D.6), the equilibrium relation between the reservation dividend and probability of sale in the no-counteroffer scenario (3.D.10), and the derivative of the probability of sale in the no-counteroffer scenario with respect to the asking price with a uniformly distributed idiosyncratic dividend (3.D.14):

$$r(d) \;=\; p(d) + \frac{\gamma_n(p(d))}{\partial \gamma_n / \partial p \;|_{p=p(d)}} \tag{3.D.29}$$

$$\;=\; p(d) - \frac{\beta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon_n^*(d)). \tag{3.D.30}$$

Then,

$$\frac{\partial r}{\partial d} = \frac{\partial p}{\partial d} + \frac{\beta}{1-\pi\beta}\frac{\partial \varepsilon_n^*}{\partial d} \tag{3.D.31}$$

$$= \frac{2\beta^2\theta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d))\left(-\frac{\partial \varepsilon_n^*}{\partial d}\right) < 0, \tag{3.D.32}$$

where the second line follows from (3.D.28). The expected sales price $E[\textit{Sales price}(d)] = \theta p(d) + (1-\theta)r(d)$ is decreasing with distance to the city center, as both the asking price $p(d)$ and the seller reservation value $r(d)$ are decreasing with distance to the city center. □

Time on the market. The probability $\gamma_{nc}(p(d))$ that an apartment sells in a period is given via the probabilities for the two bargaining scenarios and the corresponding probabilities of sale:

$$\gamma_{nc}(p(d)) = \theta\gamma_n(p(d)) + (1-\theta)\gamma_c(p(d)). \tag{3.D.33}$$

The expected time on the market (in days) at a given distance to the city center d is

$$E[TOM(d)] = \frac{1}{\gamma_{nc}(p(d))} = \frac{1}{\theta\gamma_n(p(d)) + (1-\theta)\gamma_c(p(d))}. \tag{3.D.34}$$

Proposition 3. The expected time on the market $E[TOM(d)]$ increases with distance to the city center d in the extended model with bargaining.

Proof. Using Lemma 3.2 and the equilibrium relations between the reservation dividends and the probabilities of sale (3.D.10) and (3.D.11), we can express the expected time on the market only in terms of the reservation dividend in the no-counteroffer scenario:

$$E[TOM(d)] = \frac{1}{(2-\theta)(\tilde{\varepsilon} - \varepsilon_n^*(d))}. \tag{3.D.35}$$

The derivative of the expected time on the market with respect to the distance to the city center amounts to

$$\frac{\partial E[TOM]}{\partial d} = \underbrace{-\left((2-\theta)(\tilde{\varepsilon} - \varepsilon_n^*(d))\right)^{-2}}_{<0}\left(\underbrace{-(2-\theta)}_{<0}\frac{\partial \varepsilon_n^*}{\partial d}\right). \tag{3.D.36}$$

□

Intuition. See main text.

Asking price discount. The expected asking price discount at a given distance to the city center is

$$E[Discount(d)] = \theta \cdot Discount_n(d) + (1-\theta) \cdot Discount_c(d) = (1-\theta) \cdot Discount_c(d), \tag{3.D.37}$$

where the asking price discount in the no-counteroffer scenario is $Discount_n(d) = 0$ and the asking price discount in the counteroffer scenario is $Discount_c(d)$. We define the asking price discount in the counteroffer scenario analogously to our empirical measure as

$$Discount_c(d) = \frac{r(d) - p(d)}{p(d)}. \tag{3.D.38}$$

Proposition 4. Given that the probability of no counteroffer $\theta \in (0,1)$, the expected asking price discount $E[Discount(d)] < 0$ decreases with distance to the city center d.

Proof. If $\theta = 1$, then the asking price discount is always equal to zero, as the probability of being in the no-counteroffer scenario is equal to one, and hence the asking price is the same as the sales price at all distances to the city center. This corresponds to the setup in the main model. In the following, we consider $\theta < 1$. Plugging in the optimal reservation value $r(d)$ of a seller from (3.D.7), we have that

$$Discount_c(d) = \frac{\frac{\beta\theta\gamma_n(d)p(d)}{1-\beta(1-\theta\gamma_n(p(d)))} - p(d)}{p(d)} \tag{3.D.39}$$

$$= -\frac{1-\beta}{1-\beta+\beta\theta(\tilde{\varepsilon}-\varepsilon_n^*(d))} < 0, \tag{3.D.40}$$

using the equilibrium relation between the reservation dividend and the probability of sale (3.D.10) in the second line. Hence, we also have that the expected asking price discount $E[Discount(d)] = (1-\theta)Discount_c(d) < 0$. The derivative of the expected asking price discount with respect to the distance to the city center amounts to

$$\frac{\partial E[Discount]}{\partial d} = \underbrace{-(1-\theta)(\beta-1)\left(1-\beta+\beta\theta(\tilde{\varepsilon}-\varepsilon_n^*(d))\right)^{-2}}_{>0}\left(\underbrace{-\beta\theta}_{<0}\frac{\partial\varepsilon_n^*}{\partial d}\right). \tag{3.D.41}$$

This expression is negative, provided that $\theta > 0$, as the reservation dividend $\varepsilon_n^*(d)$ increases with distance to the city center x via Lemma 3.3. □

Intuition. As in the case of the time on the market, the relevant condition for liquidity to decrease with distance to the city center is that the reservation dividend increases with distance to the city center. Via this condition, we have that the asking price and the seller reservation value both decrease with distance to the city center (see Corollary 3.4). For the expected asking price discount to become more negative with distance to the city center, we need that the seller reservation value decreases more steeply across space than the asking price.[23]

Why is this condition fulfilled? Recall from the seller optimization that the reservation value is equal to discounted profits of the next period in equilibrium, as otherwise, the seller would always reject the buyer's optimal counteroffer. For the asking price discount to become more negative with distance to the city center, we, therefore, need that profits are decrease more steeply across space than asking prices.[24]

A proof of this statement follows at the end of this subsection. Intuitively, we can express profits only in terms of the probability of sale and the asking price. Since both the probability of sale and the asking price decrease with distance to the city center and profits are composed of the two, profits decrease more steeply with distance to the city center than the asking price alone. All of these variables decrease with distance to the city center because buyers want to be compensated for commuting costs via higher reservation dividends.

Relating this insight back to the asking price discount, we know that the seller reservation value decreases more steeply than the asking price because discounted profits decrease more steeply than the asking price. Hence, the expected asking price discount is decreasing with distance to the city center.

Proof: profits decrease more steeply across space than asking prices. From the seller problem (3.D.5), we have that in an equilibrium, we can express profits as

23. Formally,

$$\frac{\partial E[Discount]}{\partial d} = (1-\theta)\frac{\partial(\frac{r-p}{p})}{\partial d} = (1-\theta)\left(\frac{\partial r}{\partial d}\frac{1}{p(d)} - \frac{\partial p}{\partial d}\frac{r}{p^2}\right), \tag{3.D.42}$$

such for the expected discount to be decreasing with distance to the city center, we need

$$\underbrace{\frac{\partial r/\partial d}{r(d)}}_{<0} < \underbrace{\frac{\partial p/\partial d}{p(d)}}_{<0}, \tag{3.D.43}$$

where both sides of the expression are < 0 due to Corollary 3.4.

24. Formally,

$$\frac{\partial r/\partial d}{r(d)} = \frac{\partial(\beta\Pi)/\partial d}{\beta\Pi(d)} = \frac{\partial\Pi/\partial d}{\Pi(d)} < \frac{\partial p/\partial d}{p(d)}. \tag{3.D.44}$$

$$\begin{aligned} \Pi(d) &= \theta\gamma_n(\cdot)p(d) + (1-\theta\gamma_n(\cdot))r(d) \\ &= \theta\gamma_n(\cdot)p(d) + (1-\theta\gamma_n(\cdot))\beta\Pi(d), \end{aligned} \tag{3.D.45}$$

since the seller's reservation value $r(d) = \beta\Pi(d)$ via the optimal counteroffer of the buyer. Then,

$$\Pi(d) = \frac{\theta\gamma_n(\cdot)p(d)}{1-\beta+\theta\beta\gamma_n(\cdot)} \tag{3.D.46}$$

and

$$\frac{\partial\Pi}{\partial d} = \frac{(1-\beta+\theta\beta\gamma_n(\cdot))(\theta\frac{\partial\gamma_n}{\partial d}p(d) + \theta\gamma(\cdot)\frac{\partial p}{\partial d}) - \theta^2\beta\frac{\partial\gamma_n}{\partial d}\gamma_n(\cdot)p(d)}{(1-\beta+\theta\beta\gamma_n(\cdot))^2}. \tag{3.D.47}$$

The proportional derivative of profits with respect to the distance to the city center is then

$$\begin{aligned} \underbrace{\frac{\partial\Pi/\partial d}{\Pi(d)}}_{<0} &= \frac{(1-\beta+\theta\beta\gamma_n(\cdot))(\theta\frac{\partial\gamma}{\partial d}p(d) + \theta\gamma(\cdot)\frac{\partial p}{\partial d}) - \theta^2\beta\frac{\partial\gamma_n}{\partial d}\gamma_n(\cdot)p(d)}{\theta\gamma_n(\cdot)p(d)(1-\beta+\theta\beta\gamma_n(\cdot))} &(3.D.48) \\ &= \frac{\frac{\partial\gamma_n}{\partial d}p(d) + \frac{\partial p}{\partial d}\gamma_n(\cdot)}{\gamma_n(\cdot)p(d)} - \frac{\theta\beta\frac{\partial\gamma_n}{\partial d}}{1-\beta+\theta\beta\gamma_n(\cdot)} &(3.D.49) \\ &= \underbrace{\frac{\partial\gamma_n/\partial d}{\gamma(\cdot)}}_{<0} + \underbrace{\frac{\partial p/\partial d}{p(d)}}_{<0} - \underbrace{\frac{\theta\beta\frac{\partial\gamma_n}{\partial d}}{1-\beta+\theta\beta\gamma_n(\cdot)}}_{<0}. &(3.D.50) \end{aligned}$$

Statement (3.D.44) says that

$$\frac{\partial\Pi/\partial d}{\Pi(d)} < \frac{\partial p/\partial d}{p(d)}, \tag{3.D.51}$$

for which to hold we therefore need that

$$\frac{\partial\gamma_n/\partial d}{\gamma_n(\cdot)} < \frac{\theta\beta\frac{\partial\gamma_n}{\partial d}}{1-\beta+\theta\beta\gamma_n(\cdot)}. \tag{3.D.52}$$

As $\frac{\partial\gamma_n}{\partial d} < 0$, this expression simplifies to

$$\frac{1}{\gamma_n(\cdot)} > \frac{\theta\beta}{1-\beta+\theta\beta\gamma_n(\cdot)}, \tag{3.D.53}$$

or

$$1-\beta > 0, \tag{3.D.54}$$

which is true, since $\beta \in (0,1)$. Therefore, $\frac{\partial\Pi/\partial d}{\Pi(d)} < \frac{\partial p/\partial x}{p(d)}$, as required. □

Relation between time on the market and asking price discount. Via the proofs of Propositions 3 and 4, we can directly derive that apartments that spend more time on the market also sell at more negative discounts. Thus, lower liquidity in one measure corresponds to lower liquidity in the other measure, and the two measures of liquidity are interchangeable in the model.

Corollary 3.5. *Given that the probability of no counteroffer $\theta \in (0,1)$, the model correlation between the expected time on the market $E[TOM(d)]$ and the expected asking price discount $E[Discount(d)]$ is negative.*

Proof. We start by expressing the time on the market as a function of the asking price discount. Then, we evaluate the derivative of the time on the market with respect to the discount at a given distance to the city center. First, from the proofs of Propositions 3 and 4 we have that

$$\tilde{\varepsilon} - \varepsilon_n^*(d) = \frac{1}{(2-\theta)E[TOM(d)]} = \frac{1}{\beta\theta}\left(\frac{(\beta-1)(1-\theta)}{E[Discount(d)]} - 1 + \beta\right). \tag{3.D.55}$$

We can hence express the relation between the expected time on the market and the expected asking price discount as

$$E[TOM(d)] = \frac{\beta\theta}{2-\theta}\left(\frac{(\beta-1)(1-\theta)}{E[Discount(d)]} - 1 + \beta\right)^{-1}. \tag{3.D.56}$$

The derivative of expected time on the market with respect to the expected asking price discount, evaluated at a given distance to the city center $\bar{d}$ is then

$$\left.\frac{\partial E[TOM]}{\partial E[Discount]}\right|_{d=\bar{d}} = \underbrace{-\frac{\beta\theta}{2-\theta}}_{<0}\underbrace{\left(\frac{(\beta-1)(1-\theta)}{E[Discount(\bar{d})]} - 1 + \beta\right)^{-2}}_{>0}\underbrace{\left(-\frac{(\beta-1)(1-\theta)}{\left(E[Discount(\bar{d})]\right)^2}\right)}_{>0} < 0, \tag{3.D.57}$$

provided that $\theta \in (0,1)$. A less negative asking price discount corresponds to a lower time on the market. □

Appendix 3.E Equilibrium existence and uniqueness

We show existence and uniqueness of an equilibrium in the extended model. The main model can be obtained by setting the probability of the no-counteroffer scenario $\theta = 1$.

3.E.1 Equilibrium existence

First, we argue for the existence of a solution. Evidently, we find a solution numerically, nevertheless, we prove the existence formally, following Krainer (2001). Via (3.11), we can express the buyer's value function as

$$V_m(d,\varepsilon) \;=\; \frac{\beta}{1-\pi\beta}\Big(\varepsilon-\tau(d)+(1-\pi)(\Pi(d)+W)\Big). \tag{3.E.1}$$

Hence, $V_m(d,\varepsilon)$ is linear in ε and there exist reservation dividends given the linear buyer indifference conditions (3.D.8) and (3.D.9). In what follows, we express the other endogenous equilibrium objects in terms of the buyer's reservation dividends and the set of model parameters to show the uniqueness of the solution. We then have expressions that only depend on the reservation dividends, given a set of parameters. The fact that reservation dividends exist then implies that a model solution also exists.

3.E.2 Equilibrium uniqueness

To show the uniqueness of the model's solution, we follow Vanhapelto and Magnac (2023). The strategy for the proof of uniqueness is as follows. We show that two possible ways of expressing the value of search allow for only one value of the idiosyncratic reservation dividend (at each distance to the city center) such that both of these expressions hold. The first expression decreases in the idiosyncratic reservation dividends, whereas the second expression increases in the idiosyncratic reservation dividends. Hence, given a set of parameters, the model's solution is unique, as first, only one idiosyncratic reservation dividend can fulfill both of these conditions and second, we express all endogenous model variables in terms of parameters and the idiosyncratic reservation dividend.

The value of search decreases in the reservation dividend. We set up the first expression for the value of search in terms of the buyer's reservation dividends via the definitions (3.D.2), (3.D.3), and (3.D.4):

$$\begin{aligned} W \;&=\; E_{d,\varepsilon}\left[\theta V_n(d,\varepsilon)+(1-\theta)V_c(d,\varepsilon)\right] && \text{(3.E.2)}\\ &=\; E_{d,\varepsilon}\left[\theta\max\left[V_m(d,\varepsilon)-p(d),\beta W\right]+(1-\theta)\max\left[V_m(d,\varepsilon)-r(d),\beta W\right]\right], && \text{(3.E.3)}\end{aligned}$$

and hence

$$W-\beta W \;=\; E_{d,\varepsilon}\left[\theta\max\left[V_m(d,\varepsilon)-p(d)-\beta W,0\right]+(1-\theta)\max\left[V_m(d,\varepsilon)-r(d)-\beta W,0\right]\right], \tag{3.E.4}$$

which simplifies to

$$W = \frac{1}{1-\beta}E_{d,\varepsilon}\left[\theta \max[V_m(d,\varepsilon) - p(d) - \beta W, 0] + (1-\theta)\max[V_m(d,\varepsilon) - r(d) - \beta W, 0]\right]. \tag{3.E.5}$$

We now express the relations within the max operators in terms of the buyer's reservation dividends. Note that when the buyer indifference conditions (3.D.8) and (3.D.9) hold, we have that

$$\beta W = V_m(d, \varepsilon_n^*(d)) - p(d) = V_m(d, \varepsilon_c^*(d)) - r(d). \tag{3.E.6}$$

Inserting the linear buyer value function from (3.E.1), we get

$$\begin{aligned}\beta W &= \frac{\beta}{1-\pi\beta}\Big(\varepsilon_n^*(d) - \tau(d) + (1-\pi)(\Pi(d) + W)\Big) - p(d) && (3.E.7)\\ &= \frac{\beta}{1-\pi\beta}\Big(\varepsilon_c^*(d) - \tau(d) + (1-\pi)(\Pi(d) + W)\Big) - r(d). && (3.E.8)\end{aligned}$$

Hence,

$$\frac{\beta}{1-\pi\beta}\varepsilon_n^*(d) = \frac{\beta}{1-\pi\beta}\tau(d) - \frac{\beta(1-\pi)}{1-\pi\beta}\Pi(d) + \frac{\pi\beta(1-\beta)}{1-\pi\beta}W + p(d) \tag{3.E.9}$$

and

$$\frac{\beta}{1-\pi\beta}\varepsilon_c^*(d) = \frac{\beta}{1-\pi\beta}\tau(d) - \frac{\beta(1-\pi)}{1-\pi\beta}\Pi(d) + \frac{\pi\beta(1-\beta)}{1-\pi\beta}W + r(d). \tag{3.E.10}$$

Using the linear buyer value function from (3.E.1), we can express the sum within the first max operator from (3.E.5) as

$$\begin{aligned}V_m(d,\varepsilon) - p(d) - \beta W =& \frac{\beta}{1-\pi\beta}\Big(\varepsilon - \tau(d) + (1-\pi)(\Pi(d) + W)\Big) - p(d) - \beta W && (3.E.11)\\ =& \frac{\beta}{1-\pi\beta}\varepsilon + -\frac{\beta}{1-\pi\beta}\tau(d) + \frac{\beta(1-\pi)}{1-\pi\beta}\Pi(d) - p(d) - \frac{\pi\beta(1-\beta)}{1-\pi\beta}W.\end{aligned}$$

Then, via (3.E.9), we get

$$V_m(d,\varepsilon) - p(d) - \beta W = \frac{\beta}{1-\pi\beta}\varepsilon - \frac{\beta}{1-\pi\beta}\varepsilon_n^*(d) = \frac{\beta}{1-\pi\beta}(\varepsilon - \varepsilon_n^*(d)). \tag{3.E.12}$$

Analogously, using (3.E.10), we have that

$$V_m(d,\varepsilon) - r(d) - \beta W \;=\; \frac{\beta}{1-\pi\beta}(\varepsilon - \varepsilon_c^*(d)). \tag{3.E.13}$$

We can then express the value of search from (3.E.5) as

$$W \;=\; \frac{1}{1-\beta}E_{d,\varepsilon}\left[\theta\max\left[\frac{\beta}{1-\pi\beta}(\varepsilon-\varepsilon_n^*(d)),0\right] + (1-\theta)\max\left[\frac{\beta}{1-\pi\beta}(\varepsilon-\varepsilon_c^*(d)),0\right]\right] \tag{3.E.14}$$

$$=\; \frac{1}{1-\beta}\frac{\beta}{1-\pi\beta}\Big(\theta E_{d,\varepsilon}\Big[\max\big[(\varepsilon-\varepsilon_n^*(d)),0\big]\Big] + (1-\theta)E_{d,\varepsilon}\Big[\max\big[(\varepsilon-\varepsilon_c^*(d)),0\big]\Big]\Big) \tag{3.E.15}$$

$$=\; \frac{1}{1-\beta}\frac{\beta}{1-\pi\beta}\Big(\theta E_{d,\varepsilon}\Big[(\varepsilon-\varepsilon_n^*(d))\mathbb{1}_{\varepsilon\geq\varepsilon_n^*(d)}\Big] + (1-\theta)E_{d,\varepsilon}\Big[(\varepsilon-\varepsilon_c^*(d))\mathbb{1}_{\varepsilon\geq\varepsilon_c^*(d)}\Big]\Big), \tag{3.E.16}$$

which decreases in $\varepsilon_n^*(d)$ and $\varepsilon_c^*(d)$.

The value of search increases in the reservation dividend. We set up the second expression for the value of search via the buyer indifference conditions (3.D.8) and (3.D.9). Via (3.D.8), we have that

$$V_m(d,\varepsilon_n^*(d)) - p(d) \;=\; \beta W \tag{3.E.17}$$

for the no-counteroffer scenario. Hence, using the linear buyer value function from (3.E.1), we can express this condition as

$$\frac{\beta}{1-\pi\beta}\big(\varepsilon_n^*(d) - \tau(d) + (1-\pi)(\Pi(d)+W)\big) - p(d) \;=\; \beta W, \tag{3.E.18}$$

and obtain

$$W \;=\; \frac{1}{\pi-\pi\beta}\left(\varepsilon_n^*(d) - \tau(d) + (1-\pi)\Pi(d) - \frac{1-\pi\beta}{\beta}p(d)\right). \tag{3.E.19}$$

Via Lemma 3.3, we have that

$$p(d) \;=\; \frac{\beta}{1-\pi\beta}(\tilde{\varepsilon} - \varepsilon_n^*(d)) + \frac{\beta^2\theta}{(1-\beta)(1-\pi\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d))^2$$

and

$$\Pi(d) = \frac{\beta\theta}{(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d))^2.$$

Then, we are able to calculate the derivative of the value of search with respect to the reservation dividend and show that it is positive. Via (3.E.19), we have that

$$\begin{aligned}
\frac{\partial W}{\partial \varepsilon_n^*} &= \frac{1}{\pi - \pi\beta} + \frac{1-\pi}{\pi - \pi\beta}\frac{\partial \Pi}{\partial \varepsilon_n^*} - \frac{1-\pi\beta}{\beta(\pi - \pi\beta)}\frac{\partial p}{\partial \varepsilon_n^*} && (3.E.20)\\
&= \frac{1}{\pi - \pi\beta} - \frac{2(1-\pi)\beta\theta}{(\pi - \pi\beta)(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d))\\
&\quad + \frac{1}{\pi - \pi\beta} + \frac{2(1-\pi\beta)\beta\theta}{(\pi - \pi\beta)(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d)) && (3.E.21)\\
&= \frac{2}{\pi - \pi\beta} + \frac{2\pi\beta\theta}{(\pi - \pi\beta)(1-\pi\beta)}(\tilde{\varepsilon} - \varepsilon_n^*(d)) > 0. && (3.E.22)
\end{aligned}$$

Via the buyer indifference condition from the counteroffer scenario (3.D.9), we have that

$$V_m(d, \varepsilon_c^*(d)) - r(d) = \beta W. \tag{3.E.23}$$

Going through the same steps as before yields

$$W = \frac{1}{\pi - \pi\beta}\left(\varepsilon_c^*(d) - \tau(d) + (1-\pi)\Pi(d) - \frac{1-\pi\beta}{\beta}r(d)\right) \tag{3.E.24}$$

for the value of search. Via (3.D.6), (3.D.14), and (3.D.18), the seller's reservation value amounts to

$$\begin{aligned}
r(d) &= -\frac{(1-\beta)\gamma_n(p(d)) + \beta\theta\gamma_n^2(p(d))}{(1-\beta)\partial\gamma_n/\partial p\ |_{p=p(d)}} + \frac{\gamma_n(p(d))}{\partial\gamma_n/\partial p\ |_{p=p(d)}} && (3.E.25)\\
&= \frac{\beta^2\theta}{(1-\pi\beta)(1-\beta)}\gamma_n^2(p(d)) && (3.E.26)
\end{aligned}$$

and via Lemma 3.2, we get

$$\begin{aligned}
r(d) &= \frac{\beta^2\theta}{(1-\pi\beta)(1-\beta)}\left(\frac{1}{2}\gamma_c(p(d))\right)^2 && (3.E.27)\\
&= \frac{\beta^2\theta}{4(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon} - \varepsilon_c^*(d))^2 && (3.E.28)
\end{aligned}$$

and we can reformulate profits as

$$\Pi(d) \;=\; \frac{\beta\theta}{4(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon}-\varepsilon_c^*(d))^2. \tag{3.E.29}$$

Then, via (3.E.24), the derivative of the search value with respect to the reservation dividend in the buyer's price scenario amounts to

$$\begin{aligned}
\frac{\partial W}{\partial \varepsilon_c^*} =& \frac{1}{\pi-\pi\beta}+\frac{1-\pi}{\pi-\pi\beta}\frac{\partial \Pi}{\partial \varepsilon_c^*}-\frac{1-\pi\beta}{\beta(\pi-\pi\beta)}\frac{\partial r}{\partial \varepsilon_c^*} && (3.E.30)\\
=& \frac{1}{\pi-\pi\beta}-\frac{(1-\pi)\beta\theta}{2(\pi-\pi\beta)(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon}-\varepsilon_c^*(d))\\
&+\frac{(1-\pi\beta)\beta\theta}{2(\pi-\pi\beta)(1-\pi\beta)(1-\beta)}(\tilde{\varepsilon}-\varepsilon_c^*(d)) && (3.E.31)\\
=& \frac{1}{\pi-\pi\beta}+\frac{\pi\beta\theta}{2(\pi-\pi\beta)(1-\pi\beta)}(\tilde{\varepsilon}-\varepsilon_c^*(d)) \;>\; 0. && (3.E.32)
\end{aligned}$$

Since the first expression for the value of search decreases in the reservation dividends and the second one is increases in the reservation dividends, there can only be a single pair of reservation dividends to solve the model such that these conditions are fulfilled. Additionally, since the value of search does not depend on the distance to the city center, whereas the reservation dividends do, this relation holds for all distances to the city center. There is hence also a unique value of search that allows to obtain a spatial equilibrium.

Appendix 3.F Additional model results

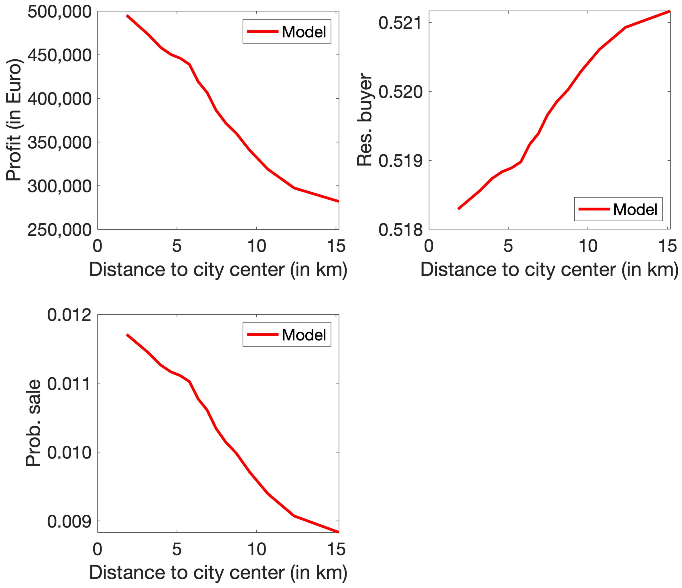


Figure 3.F.1. Hamburg: spatial distributions of other endogenous variables

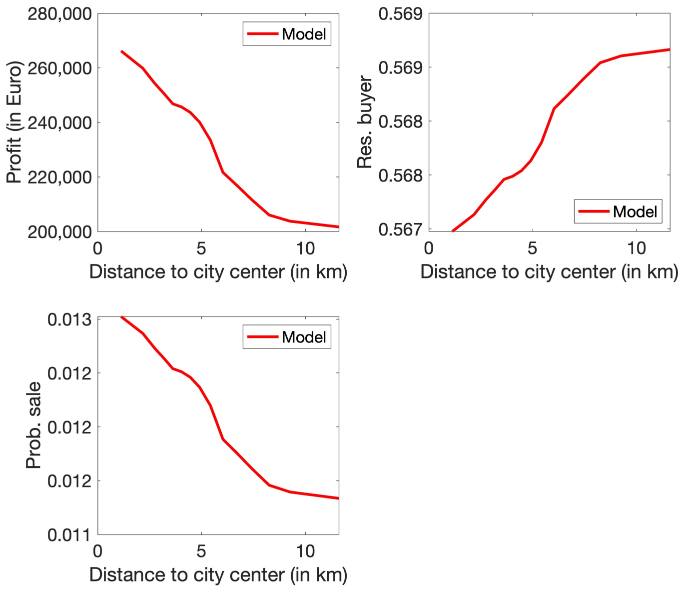


Figure 3.F.2. Cologne: spatial distributions of other endogenous variables

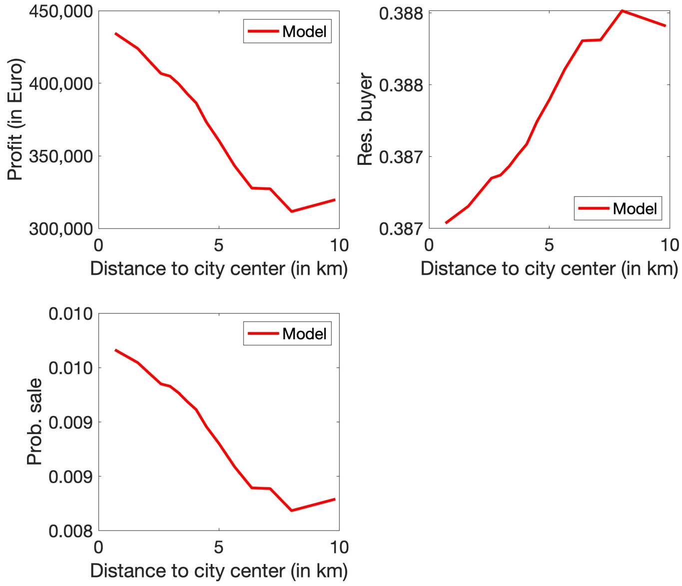


Figure 3.F.3. Frankfurt: spatial distributions of other endogenous variables

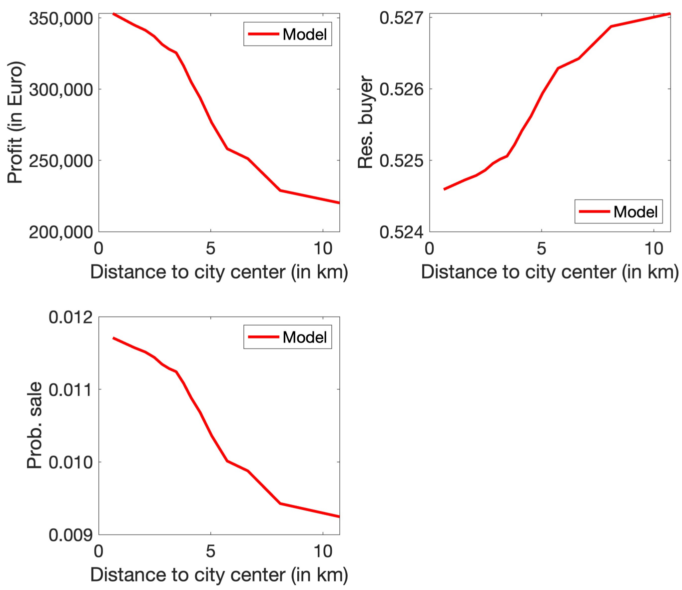


Figure 3.F.4. Duesseldorf: spatial distributions of other endogenous variables

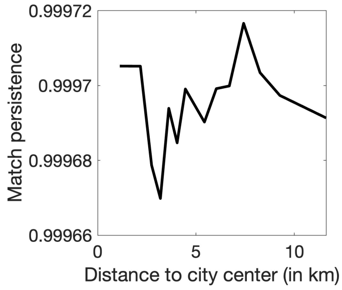


Figure 3.F.5. Cologne: housing match persistence π across space

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Chapter 4

Interest rates and the spatial polarization of housing markets*

Joint with Martin Dohmen, Sebastian Kohl, and Moritz Schularick

4.1 Introduction

In 1980, the median home in Scranton, PA, was worth more than half the median home in New York City. By 2018, its value had decreased to one fifth of the New York City home according to U.S. Census data. In the U.S. and internationally, there has been a substantial increase in regional housing price differences since the 1980s (Van Nieuwerburgh and Weill, 2010; Hilber and Mense, 2021). The spatial structure of economic activity has changed considerably across countries in recent decades. A prominent trend is increasing social and spatial polarization among different sub-national housing markets. As housing is the most important asset for most households, the increasing dispersion of housing prices and housing wealth have become the subject of intense public debate.[1]

From an economic point of view, rising price dispersion across segmented housing markets could increase spatial misallocation of labor as productive workers are

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1. For instance, existing homeowners in high price urban areas have an incentive to restrict urban growth to the detriment of new buyers (Ortalo-Magné and Prat, 2014). The increasing polarization of housing wealth may have also contributed to political polarization at the national level (Adler and Ansell, 2019; Ansell, 2019).

forced to stay in places where housing is still affordable. For instance, Hsieh and Moretti (2019) estimate that such misallocation slowed down the growth rate of U.S. GDP by one third in past decades. An increase in local housing prices has also been shown to lead to more misallocation of capital (Herkenhoff, Ohanian, and Prescott, 2018), to affect local non-tradable employment (Mian and Sufi, 2014) and demand conditions (Mian and Sufi, 2011; Mian, Rao, and Sufi, 2013; Guren et al., 2020), as well as consumer prices (Stroebel and Vavra, 2019).

Why have housing prices risen more in some locations than in others? In the most parsimonious framework, rental cash flows determine the value of housing assets: the price of a house is equivalent to the discounted expected future rental cash flow it generates (Poterba, 1984). An important implication – and the starting point for most existing explanations of growing housing price dispersion – is that price and rent dispersion should evolve in lockstep. Yet, as we will show, this approach is at odds with an important stylized fact: rent dispersion has increased considerably less than price dispersion in recent decades, both in the U.S. and internationally. Existing studies that model housing price dispersion as a function of growing differences in local rents (e.g. Van Nieuwerburgh and Weill, 2010; Gyourko, Mayer, and Sinai, 2013b) typically overestimate changes in rent dispersion by a substantial margin.

We use a novel long-run data set of housing prices and rents for 27 major agglomerations in 15 developed countries as well as long-run data covering the entire cross-section of U.S. MSAs, and show that price–rent ratios in large agglomerations have increased about twice as much as the national average since the 1980s. Moreover, new research using granular transaction data suggest that the disconnect between rent and price dispersion is not driven by measurement error due to market segmentation between owner-occupied and rental housing (Begley, Loewenstein, and Willen, 2021; Demers and Eisfeldt, 2021).

We propose a novel explanation that allows for increasing dispersion of within-country housing prices despite much smaller increases in rent dispersion, and ultimately even without changes in rents altogether. In essence, we argue that a decline in real risk-free interest rates will have differential effects on housing prices if there is heterogeneity in initial rent–price ratios across housing markets within an economy. U.S. and international data provide ample evidence for such differences in rental yields across regions. Importantly, large agglomerations exhibit systematically lower rent–price ratios than smaller cities and more remote regions (Demers and Eisfeldt, 2021; Hilber and Mense, 2021). Such differences in rent–price ratios can be generated either by spatial heterogeneity in housing risk, or by differences in local rent growth expectations.[2] Empirically, the presence of higher hous-

2. Note that this holds under more general conditions. Using a simple discount rate – cash flow decomposition (Campbell and Shiller, 1988), differences in rent–price ratios are driven by local rent growth expectations or by differences in local housing discount rates.

ing risk premia outside the large agglomerations has been demonstrated by Amaral et al. (2021b). There is limited evidence on rent growth expectations on the regional level, but realized rent growth does not seem to differ much between the major agglomerations and the national average (Van Nieuwerburgh and Weill, 2010; Amaral et al., 2021b). Note, however, that for our proposed mechanism the source of the heterogeneity in initial rent–price ratios is irrelevant.

To rationalize how the well-documented decline in real safe interest rates since the 1980s (Holston, Laubach, and Williams, 2017; Negro et al., 2019) has boosted economy-wide housing price dispersion in the presence of initial difference in rent–price ratios, we turn to a spatial version of the Gordon growth model (Gordon, 1962).[3] We integrate heterogeneity in risk premia and rent growth expectations across regions in the present-value equation for housing prices and show that a fall in real discount rates disproportionately affects the valuation of housing in cities in which initial rent–price ratios are low. This is because a fall in discount rates leads to a linear fall in rent–price ratios but a non-linear increase in the price–rent ratio as the inverse function of the rent–price ratio. With lower initial levels in larger agglomerations such as New York City, a fall in economy-wide real safe interest rate leads to stronger increases in the price–rent ratios in these places and to an increase in economy-wide housing price dispersion without concomitant rent dispersion.

In a last step, we calibrate our model to the data and demonstrate that it can generate an increase in prices as well as increasing dispersion of price–rent ratios similar to the observational data. Quantitatively, a fall of the real discount rate of 1.3 percentage points between 1985 and 2018 generates the rise in real housing prices and their dispersion observed in our sample of 27 large agglomerations. A 1.3 percentage points fall is close to existing estimates that point to a fall in real housing discount rates of around 1 and 1.1 percentage points over a similar period (Bracke, Pinchbeck, and Wyatt, 2018; Kuvshinov and Zimmermann, 2020). Note that the fall in real discount rates was less pronounced than the fall in the real safe rate, as there is evidence that risk-premia increased over this period (Caballero, Farhi, and Gourinchas, 2017).

We are not the first to link the rise in real housing prices to declining real interest rates on the national level (Garriga, Manuelli, and Peralta-Alva, 2019; Miles and Monro, 2019). Yet, to the best of our knowledge, our study is the first to make the point that, in the presence of initial heterogeneity in rent–price ratios, declining real risk-free interest rates can not only explain rising overall real housing prices, but also growing housing price dispersion. Related work by Kroen et al. (2021) for the stock market shows that falling real interest rates contribute to the rise of superstar firms, especially when interest rate levels are low.

3. In Figure 4.E.1, we plot the evolution of real safe rates for the U.S. and the world using the estimates from Negro et al. (2019). Safe rates display a continuous downward trend since the mid-1980s.

The remainder of this paper is organized as follows. The following section examines existing explanations for the increase in housing price dispersion and the evidence suggesting that these explanations are insufficient. Section 4.2.2 presents new empirical evidence that housing price dispersion has notably increased more than rent dispersion since the 1980s. The subsequent section presents the new mechanism and confirms that it matches the empirical evidence and can generate the excess price dispersion observed in the data. The final section concludes.

4.2 Polarization of housing markets

Table 4.1 shows the price ratio between the most expensive and the median city as well as the coefficient of variation of housing prices for cities in the U.S., Sweden, Germany and the UK in 1980 and today. The ratio of the most expensive to the median housing price region, and the change in the coefficient of variation tell a consistent story: in the U.S. and internationally, price dispersion in housing markets has increased substantially since the 1980s. Rising polarization and its causes have attracted considerable attention in the spatial and urban economics literature, e.g., Glaeser and Gyourko (2002), Quigley and Raphael (2005), Glaeser, Gyourko, and Saiz (2008), Saks (2008), Saiz (2010), Van Nieuwerburgh and Weill (2010), Gyourko, Mayer, and Sinai (2013b), Favara and Imbs (2015), Hilber and Vermeulen (2016), Been, Ellen, and O'Regan (2018), Oikarinen et al. (2018), Arundel and Hochstenbach (2019), Hilber and Mense (2021), Molloy, Nathanson, and Paciorek (2022), and Vanhapelto (2022).

Table 4.1. Price ratio of most expensive to median city & regional coefficient of variation

	Ratio (Max/Median)			Coefficient of Variation			
Country	1980	Today	Increase	1980	Today	Increase	N
USA	2.81	8.28	2.9	0.23	0.70	3.1	311
SWE	2.97*	6.14	2.1	0.31*	0.54	1.8	290
DEU	1.45	2.66	1.8	0.20	0.44	2.3	42
UK	3.19*	5.00	1.6	0.31*	0.53	1.7	307

Note: The table shows the housing price ratio of the most expensive to the median location as well as the coefficient of variation for housing prices in the U.S., Sweden, Germany and the UK in 1980 and today. The units of observation are the following: for the U.S. MSAs, for Sweden and Germany municipalities and for the U.K. local planning authorities. *: The data for Sweden starts in 1981 and for the UK in 1995. Data for today is from 2018 for the U.S. and Germany, from 2020 for the UK and from 2021 for Sweden. The coefficient of variation is defined as the ratio of the standard deviation to the mean, which are both weighted by initial population. Data sources are: U.S.: Gyourko, Mayer, and Sinai (2013b) and Amaral et al. (2021b); Sweden: Purchase price of one- and two-dwelling buildings by municipality from Statistics Sweden (Official Statistics of Sweden, 2022); Germany: Preisspiegel Immobilienverband Deutschland (Amaral et al., 2021b); UK: Median house prices for administrative geographies from the Office for National Statistics (Office for National Statistics, 2022; Office for National Statistics, UK, 2022).

4.2.1 Price dispersion in spatial housing models

In the existing literature, increasing price dispersion is typically linked to diverging housing market fundamentals across regions. In spatial housing models, price dispersion derives from the embedded present value equation for housing:

$$P_t^i = \sum_{j=1}^{\infty} \mathbb{E}\left(Rent_{t+j}^i * \left(\frac{1}{1+r_t}\right)^j\right), \tag{4.1}$$

where P_t^i is the real housing price in city i at time t, $\sum_{j=1}^{\infty} Rent_{t+j}^i$ is the stream of future real rent payments net of costs, and r_t is the real discount rate at time t. Note that we are abstracting from consumption growth in our definition of r.[4] The equation directly links current local housing prices and current and future local rents. Changes in economic fundamentals, such as wages, affect local demand for housing services and thereby rents and housing prices.

For instance, Van Nieuwerburgh and Weill (2010) construct a spatial, dynamic equilibrium model in the tradition of Rosen (1979) and Roback (1982) for the distribution of metropolitan areas in the U.S. These metropolitan areas are hit by idiosyncratic and persistent productivity shocks. Households with heterogeneous abilities move freely across metropolitan areas in reaction to these shocks. Housing supply is limited by supply regulations, meaning that rents will adjust to compensate for regional wage differences. This, in turn, determines housing prices. The authors calibrate productivity shocks to match the increase in the observed regional wage dispersion between metropolitan areas from 1975 to 2007. The model matches the increase in housing price dispersion observed in the data. However, as the authors note, it also produces an increase in rent dispersion three times larger than observed empirically.

In another well-known paper, Gyourko, Mayer, and Sinai (2013b) develop a two-location model to show that increasing national demand generated by population growth affects regions differently, depending on local housing supply elasticities. Under the assumption that people prefer to live in supply-constrained cities, the model predicts that in response to increasing national demand, supply-constrained cities will experience a stronger rental increase than unconstrained cities. This increase in rents passes through to housing prices via the present-value equation. The authors call the cities that display a combination of low supply elasticities and strong housing price growth "superstar cities". The paper does not explicitly study

4. Note that equation 4.1 can be derived from a simple consumption based asset-pricing model where investors derive utility from current and future consumption, by setting $\frac{1}{1+r_t} = \beta \frac{u'(c_{t+1})}{u'(c_t)}$, where β is the discount factor of the investor and u' its marginal utility with respect to consumption (Cochrane, 2005). To simplify, we will abstract from the influence of consumption growth on r and simply refer to r as the real discount rate.

the model predictions for rents, but in Appendix 4.A, we use the paper's data and show that prices in superstar cities increased considerably more than rents.

A partial exception to the assumption that growing housing price dispersion is a function of increasing rent dispersion is Hilber and Mense (2021). The authors use regional data for the U.K. from 1997 to 2018 and start from the empirical observation that prices have increased much more in the "superstar" city London than rents, i.e., the price–rent ratio has surged in London compared to the rest of the country. They explain this with serially correlated housing demand shocks that induce heterogeneous rent growth expectations. However, the paper is chiefly concerned with cyclical fluctuations and the proposed mechanism generates transitory divergence in price–rent ratios between regions. Over longer horizons, housing demand shocks mean-revert so that rents and prices move in lockstep (Piazzesi and Schneider, 2016).

4.2.2 Empirical evidence on price and rent dispersion

Explanations focused on rent dispersion as the source of increasing price dispersion are at odds with one important stylized fact in the data: price dispersion has increased much more than rent dispersion. Evidence for such divergent trends has not only been exposed in the U.K. data discussed above (Hilber and Mense, 2021), but also in recent U.S. data (Demers and Eisfeldt, 2021; Molloy, Nathanson, and Paciorek, 2022).

Concerns that measurement error could be responsible for the apparent divergence between rent and price growth do not appear convincing in the light of recent studies with micro data. In principle, market segmentation could lead to selection bias if rental data are typically taken from lower quality segments of the housing market while prices mainly come from higher-quality segments (Glaeser and Gyourko, 2007). However, Begley, Loewenstein, and Willen (2021) study micro-data from Corelogic on prices and rents for the same property to estimate price–rent ratios, thereby avoiding selection bias. They show that the price variation in owner- and renter-occupied housing markets are closely correlated. If anything, renter-occupied prices have risen more than owner-occupied prices. Demers and Eisfeldt (2021) also use micro-data from the American Housing Survey to build rent–price ratios for 15 different U.S. cities from 1985 to 2020. Relying on hedonic models and non-parametric methods, they show that rent–price ratios fell most strongly in "expensive" cities.

In the following, we systematize the available evidence for price and rental dispersion using two comprehensive data sets that have recently become available (Amaral et al., 2021a). One is a long-run cross country data set; the other covers the entire cross-section of regions in the U.S.. Both data sets show that dispersion in housing prices increased substantially more than dispersion in rents since the 1980s.

The first data set covers housing price series, rent series, and rent–price ratios for 27 agglomerations in 15 OECD countries over the past century. The major agglomerations are defined as the largest cities within each country in terms of 1900 population statistics, including cities like London, New York, Paris, Berlin and Tokyo. We merge the city-level series with nation-wide housing data from Jordà et al. (Replication data for: The Rate of Return on Everything, 1870-2015*) as described in Amaral et al. (2021b).

The second covers the entire cross-section of 316 MSAs in the U.S. It comprises housing prices, rents and price–rent ratios with decadal frequency from housing censuses. It is based on the data in Gyourko, Mayer, and Sinai (Replication data for: Superstar Cities), but extended to 2018 using the American Community Survey.

Figure 4.1 panel (a) plots the geometric mean of real housing price and rent increases between 1980 and 2018 for the 27 major agglomerations next to the geometric mean of national real housing price and rent increases.[5] The national means are weighted by the number of sample agglomerations in the respective country. The Figure brings two key insights. First, housing prices have grown much more than rents in both the major agglomerations and at national levels. Second, housing prices have grown considerably more in the major agglomerations than the national average. The difference in mean growth rates is as large as 70 basis points per year, which implies that mean growth rates for the agglomerations have been more than 50% higher compared to national housing price growth rates over the past four decades. With only 35 basis points the difference in yearly rent growth rates is considerably lower.

Appendix 4.B presents geometric means of housing price and rent growth rates between 1980 and 2018 by city, demonstrating that housing prices have grown more than rents in almost all economies. Housing price growth has been higher at the city-level than nationally for virtually all agglomerations in the cross-country data set. This phenomenon is particularly pronounced for the largest agglomerations, like London, New York or Paris.

Figure 4.1 panel (b) shows kernel densities for the geometric mean of housing price and rent growth rates between 1980 and 2018 by MSA for the full sample of U.S. MSAs. Housing price growth rates have not only been on average higher compared to rent growth rates, but also show more dispersion. The fat right tail of housing price growth rates is particularly striking. As discussed in Gyourko, Mayer, and Sinai (2013b) this indicates that a small set of cities had very high yearly housing price growth rates. Importantly, this is not mirrored by rent growth rates.

A necessary condition for our mechanism to hold is that rent–price ratios differ initially by cities. We mapped rent-price ratios for US MSAs in 1980. The resulting

5. We use log growth rates to calculate means and confidence intervals, such that the resulting values can be interpreted as geometric means. This way, mean values show the overall trend during the past 4 decades and are not driven by the volatility of the series.

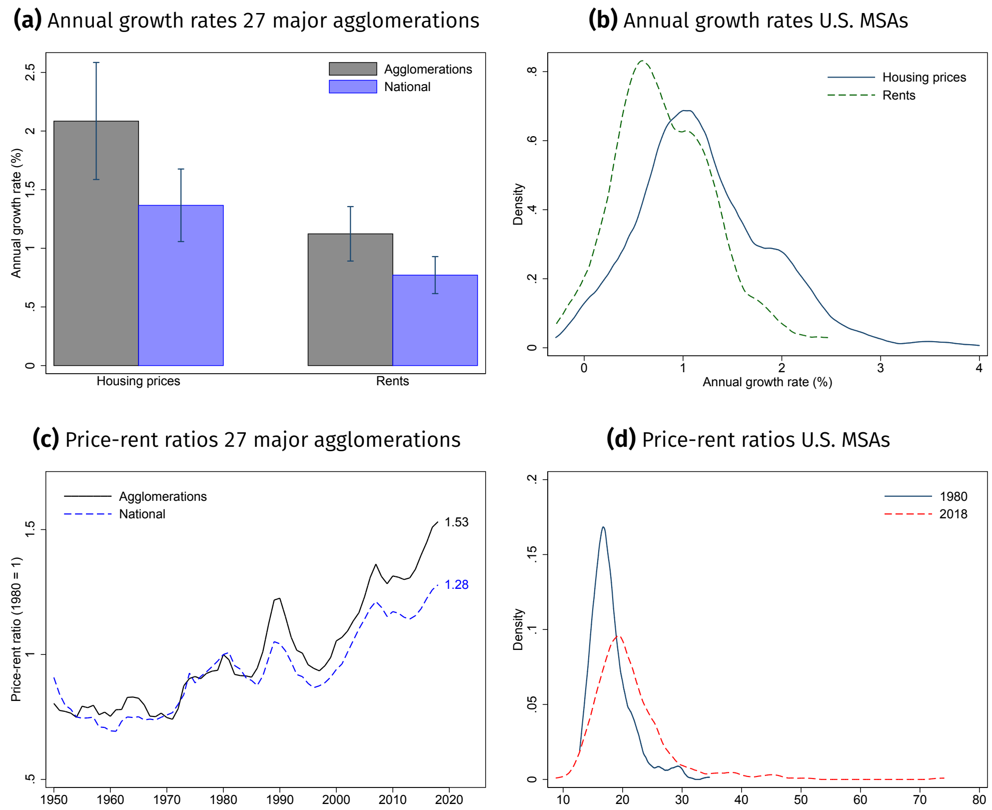

Figure 4.1. Evolution of housing price and rent growth rates and price-rent ratios between 1980 and 2018

Note: Panel (a): Geometric mean of annual housing price and rent growth rates of 27 major agglomerations (black) and the respective national averages weighted by the number of sample agglomerations in the respective country. Means and confidence intervals are calculated using log growth rates and transformed back to percentage growth rates afterwards. Panel (b): Kernel density of annualized housing price and rent growth rates between 1980 and 2018 for 316 U.S. MSAs. Panel (c): Index of equally-weighted average increases of price-rent ratios of 27 major agglomerations and average national increases of price-rent ratios weighted by the number of sample agglomerations in the respective country. 1980=1. Panel (d): Kernel density of price-rent ratios of 316 U.S. MSAs in 1980 and 2018 calculated from net rental yields.

Figure 4.E.2 in the Appendix visually shows a correlation between city size and the initial rent-price ratios and a clear geographical clustering: the regions with populous urban agglomerations at the coasts already started with considerably lower rent-price ratios in 1980 when compared to the cities in the more rural central regions.[6] Additionally, we show in Figure 4.3 that this result also holds for our international data set.

6. Demers and Eisfeldt (2021) also show substantial differences in rent-price ratios for a smaller sample of U.S. MSAs in the 1980s.

Figure 4.1 panel (c) shows the average increases in price-rent ratios over time for the 27 major agglomerations and on the national level to show the proportion of the housing price dispersion that cannot be accounted for by rent dispersion. Changes in price–rent ratios indicate how much housing prices changed after accounting for changes in rents. From previous observations, price–rent ratios are expected to have increased considerably since 1980. More importantly, the data show that price–rent ratios have increased considerably more in the major agglomerations than the national average. While the gap in price–rent ratios varies over the cycle, a phenomenon that could be explained by the mechanism proposed in Hilber and Mense (2021), it shows a strong persistence over the last decades and seems to be increasing over time. The gap starts to arise during the 1980s and does not exist in the period before. This timing coincides with the fall in the risk free rate.

Figure 4.1 panel (d) plots the distribution of U.S. MSA-level price–rent ratios in 1980 and 2018, demonstrating not only that the dispersion of price-rent ratios was already substantial in 1980, but also that it increased considerably over the last decades. Again, this phenomenon is particularly strong for the distribution's right tail, where also the major agglomerations like New York are located. As expected, mean price–rent ratios have also increased over time. Still, the coefficient of variation (CV) increased from 0.19 to 0.32.

4.3 Falling real interest rates and housing price dispersion

This section constructs a parsimonious, spatial asset-pricing model of the housing market to rationalize an increase in housing price dispersion that does not follow from increasing rent dispersion but results from differences in initial rent–price ratios between cities.

We also start from present value equation (4.1), the only difference being that we allow for differences in real discount rates between cities:

$$P_t^i = \sum_{j=1}^{\infty} \mathbb{E}\left(Rent_{t+j}^i * \left(\frac{1}{1 + r_t^i} \right)^j \right). \tag{4.2}$$

From a theoretical perspective, a combination of local market segmentation and incomplete markets implies that discount rates do not need to equalize between cities.[7] Piazzesi, Schneider, and Stroebel (2020) show that housing markets are locally segmented, using data on online searches to document large differences in housing search behavior across different municipalities in California.[8] Housing markets are also incomplete because housing assets are indivisible, and homeowners are

7. Sagi (2021) builds a housing search model, showing that heterogeneity in discount rates is an essential condition to explain the dynamics in real estate prices.

8. They also demonstrate that differences in housing search between different quality segments within municipalities are less pronounced.

typically non-diversified. The lack of diversification implies limitations to arbitrage precluding discount rates from equalizing (Piazzesi and Schneider, 2016).

Empirically, Amaral et al. (2021b) show that over the long run returns have been persistently lower in large cities than in the rest of the country. Differences in housing returns are likely due to differences in housing risk, as housing prices co-vary less with income in larger MSAs and idiosyncratic housing price risk is lower. The assumption that the discount rate differs geographically is further supported by the empirical evidence that landlords concentrate their housing portfolios close to their place of residency, exposing them to local housing market risks (Levy, 2021).

In the following, we assume that discount rates are composed of a risk-free component, that is equal for the entire country and a risk-premium that can differ by the city invested in; $r_t^i = \text{risk-free}_t + \text{risk-premium}_t^i$. To simplify the discussion, we make two additional assumptions: First, we assume that rents in city i are expected at time t to grow at a constant rate g_t^i. Second, we assume that $r_t^i > g_t^i$, such that housing prices are finite. This allows us to rewrite equation (4.2) as the Gordon (1962) growth valuation formula:

$$P_t^i = \sum_{j=1}^{\infty}\left(Rent_t^i * \left(\frac{1+g_t^i}{1+r_t^i}\right)^j\right) \qquad \Longleftrightarrow \qquad P_t^i = Rent_t^i * \frac{1+g_t^i}{r_t^i - g_t^i}. \tag{4.3}$$

Following this equation, the rent-price ratio is equal to:

$$\text{Rent-price ratio}_t^i = \frac{Rent_t^i}{P_t^i} = \frac{r_t^i - g_t^i}{1+g_t^i}. \tag{4.4}$$

We next consider a setting with two cities: agglomeration A and reservation city B. The reservation city can be understood as the average of all other locations within a country except the large agglomeration. To compare both cities, we make three additional assumptions. First, as argued in the urban economics literature (Gyourko, Mayer, and Sinai, 2013b; Hilber and Mense, 2021) we assume that expected rent growth in the large agglomeration is higher than or equal to the reservation city; $g_t^A \geq g_t^B \;\; \forall t$. Second, as argued above, we assume that risk-premia are lower or equal for housing investments in large agglomerations compared to the reservation city, such that $r_t^A \leq r_t^B \;\; \forall t$. Third, we assume that at least one of the two previous inequalities is strict, such that rent–price ratios are lower in the agglomeration and:

$$r_t^B - g_t^B > r_t^A - g_t^A > 0. \tag{4.5}$$

From equation (4.3) we can write the log price difference between cities A and B as:

$$log(P_t^A) - log(P_t^B) = log(Rent_t^A) + log\left(\frac{1+g_t^A}{r_t^A - g_t^A}\right) - log(Rent_t^B) - log\left(\frac{1+g_t^B}{r_t^B - g_t^B}\right). \tag{4.6}$$

Next we derive the predictions of our model after a fall in the real risk-free rate. We assume that the real risk-free rate decreases by Δ, such that:

$$log(P_t^A) - log(P_t^B) = \\ log(Rent_t^A) + log\left(\frac{1+g_t^A}{r_t^A - \Delta - g_t^A}\right) - log(Rent_t^B) - log\left(\frac{1+g_t^B}{r_t^B - \Delta - g_t^B}\right). \quad (4.7)$$

If we differentiate with respect to Δ and under the assumptions made above, we get:

$$\frac{\partial\left(log(P_t^A) - log(P_t^B)\right)}{\partial \Delta} = \frac{1}{r_t^A - \Delta - g_t^A} - \frac{1}{r_t^B - \Delta - g_t^B} \quad > \quad 0.$$

This demonstrates that a uniform fall in real discount rates across both cities, generated by a fall in the real risk-free rate, increases housing price dispersion if rent–price ratios initially differ.

The intuition for this observation is presented in Figure 4.2. Panel (a) plots the rent–price ratio in the model as a function of $r - g$ for a varying r, wherein the rent–price ratio changes linearly in r. Following equation (4.5), we assume that $r - g$ is lower in the agglomeration at time t, resulting in a lower rent–price ratio. Next, we assume that between t and $t+1$ r falls in both cities by one percentage point. This leads to an approximately equal fall in the rent–price ratio in the agglomeration (A) and in the reservation city (B).

(a) Rent-price ratios **(b)** Price-rent ratios

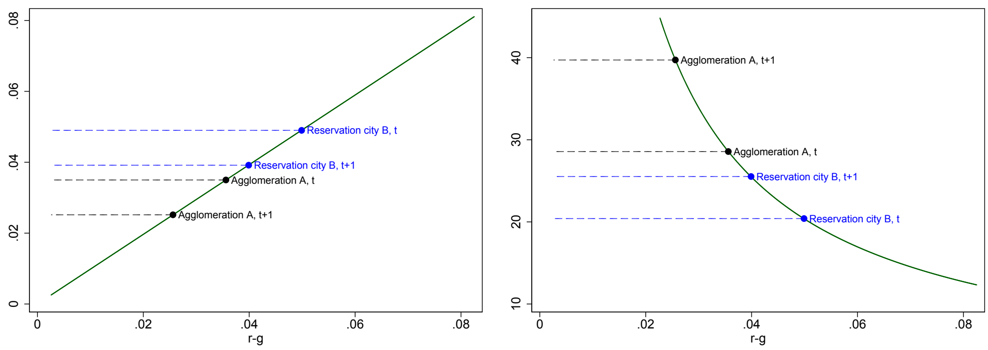

Figure 4.2. A fall in discount rates in the model

Note: Panel (a) plots the rent–price ratio in our model as a function of $r - g$. To calculate the points, we assumed that $g = 0.0175$. Panel (b) shows the corresponding price–rent ratio.

Figure 4.2 panel (b) plots the corresponding price–rent ratio. As the price–rent ratio is the inverse function of the rent–price ratio, when r changes, the price–rent ratio changes in a non-linear fashion. Since the initial price–rent ratio is higher in the agglomeration, an equally large fall in r leads to a larger increase in the price–rent ratio in the agglomeration than in the reservation city. Subsequently, the price dispersion between the agglomeration and the reservation city increases when r falls, even when rents are constant in both cities.

4.3.1 Rent–price ratios in the data

The previous section determined that price dispersion increases in response to a fall in the real risk-free rate if rent–price ratios initially differ. Our model also predicts a parallel fall in rent–price ratios across cities due to a fall in the real risk-free rate.

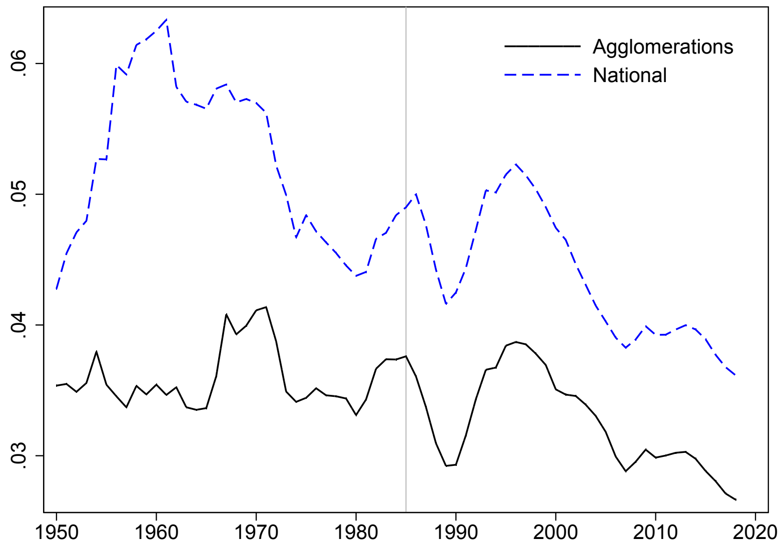

Figure 4.3. Rent–price ratios in the data

Note: The solid black line is the non-weighted average rent–price ratio of 27 major agglomerations. The dashed blue line is the average of the national rent–price ratio weighted by the number of sample agglomerations in the respective country.

Figure 4.3 plots the average rent-price ratios in the 27 major agglomerations and on the national level. Two observations are important. First, rent–price ratios have been lower in the major agglomerations over the entire period since 1950. This evidence validates the assumption regarding the initial differences in rent–price ratios.

Second, the rent–price ratios in the major agglomerations and at the national level have moved in parallel trajectories since 1985 (abstracting from the cyclical variation), suggesting a common downward trend. Rent-price ratios fell by around 1.2 percentage points from 1985 to 2018 in the major agglomerations and at the national level. The equally large fall in rent–price ratios in the major agglomerations and at the national level is equivalent to the parallel fall in rent–price ratios predicted by the model. Note that alternative mechanisms that attempt to explain the increase in price dispersion based on factors that solely affect the major agglomerations, would predict a divergence in rent–price ratios between the major agglomerations and the rest.

We also use the U.S. MSA-level data to compare the full distribution of price–rent ratios in 2018 with our model prediction. While the data align well with our proposed mechanism, there is room for other factors at play such as diverging rent growth expectations between the large agglomerations and the rest of the economy. We discuss this in more detail in Appendix 4.D.

4.4 Model calibration

To simulate the increase in price dispersion in response to a fall in r in our model, we calibrate the model to the following values. We set the expected real rent growth in the agglomeration and the reservation city equal to 1.75 %, $g_t^A = g_t^B = 0.0175 \ \ \forall t$, which is close to long-run real rent growth rates observed in our international data set.[9] Next, we assume that the real discount rate in the agglomeration is 1 percentage point lower than in the reservation city; $r_t^A = r_t^B - 0.01 \ \ \forall t$. This is equivalent to the difference in total housing returns of around 1 percentage point found in Amaral et al. (2021b). For simplification we assume that real rents in the agglomeration and in the reservation city are equal to one in period one, $Rent_1^A = Rent_1^B = 1$.

(a) Price-rent ratios as a function of r_t^A **(b)** Model predictions vs. data

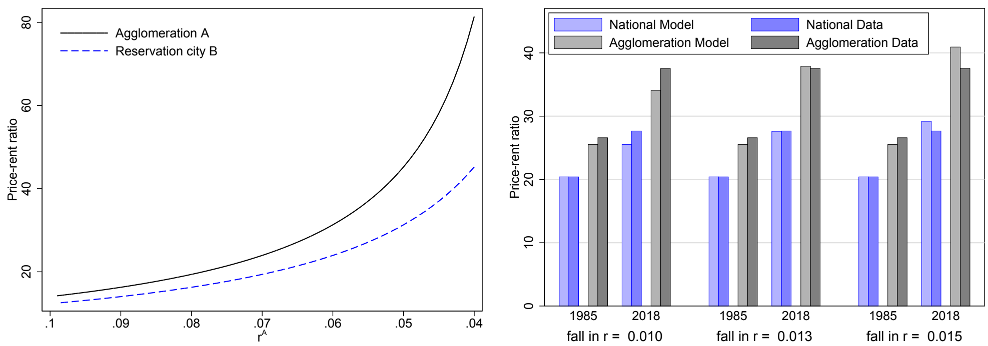

Figure 4.4. Simulated price-rent ratios in response to a fall in r

Note: Panel (a) shows price–rent ratios for the agglomeration and the reservation city in the model relative to the discount rate in the reservation city. Panel (b) compares the model to the data for different assumed values of the fall in the discount rate r. For both exercises, we assume that $g = 0.0175$ and $r^A = r^B - 0.01$.

Figure 4.4 panel (a) plots the resulting price–rent ratios in the agglomeration and reservation cities as a function of r_t^B, demonstrating that the dispersion in price–

9. Between 1950 and 2018, rents grew on average by 1.86 % in the 27 major agglomerations and by 1.65 % at the national level.

rent ratios increases when discount rates fall. Although the initial difference between the cities is small for high discount rates, the difference becomes substantial as discount rates become smaller.[10]

The next step is to assess whether our model matches the increasing levels and dispersion of price–rent ratios in the data. This requires estimates for the housing discount rates in 1985 and 2018. The estimated decline in the real risk-free rate ranges from 2.5 to 5 percentage points depending on the estimation method (Negro et al., 2019; Rachel and Summers, 2019). At the same time, there is considerable evidence that risk-premia have risen during this period, which partly offsets the effect of the fall in the risk-free rate on housing discount rates (Caballero, Farhi, and Gourinchas, 2017; Kuvshinov and Zimmermann, 2020). To the best of our knowledge, there exist two estimates for the decline in real housing discount rates over this period. Using data on U.K. leaseholds, Bracke, Pinchbeck, and Wyatt (2018) estimate a drop of around 1 percentage point between the 1990s and the 2010s for very long housing discount rates, their results are in line with Giglio, Maggiori, and Stroebel (2015), who also estimate discount rates for the housing market in Singapore.[11] Kuvshinov and Zimmermann (2020) estimate a drop of around 1.1 percentage points between 1985 and 2015 for a sample of developed countries very similar to ours.[12]

Figure 4.4 panel (b) compares the price–rent ratios predicted by our model to the actual price–rent ratios in the data for the years 1985 and 2018. We represent three scenarios for the fall in real discount rates. On the left, real discount rates fell by 1 p.p., in the middle by 1.3 p.p. and on the right by 1.5 p.p. Overall, the model slightly overshoots the price–rent ratio in the major agglomerations in 1985.[13] This indicates that the difference in risk-premia between the agglomerations and the national average was either smaller than 1 percentage point or the rent-growth expectations have been slightly higher in the major agglomerations.

In the scenario where real discount rates fall by 1 percentage point, our model cannot fully account for the rise in levels and dispersion of the price–rent ratio. It does, however, generate a substantial portion of the increase in levels and dispersion we observe in the data. Assuming a fall in r of 1.5 percentage points instead, our model does overshoot both the level and the dispersion in housing prices we observe in the data. Matching the increase in levels and dispersion in the data requires a fall in discount rates of around 1.3 percentage points.

10. The same result is demonstrated by Kroen et al. (2021) for stock markets.

11. Both papers measure discount rates for housing service flows more than 100 years in the future.

12. Our sample additionally contains Canada and our data sources differ for some specific countries. The details can be found in the Data Appendix of Amaral et al. (2021b).

13. Note that the model exactly matches the national price–rent ratio in 1985 by construction, since we back-out the initial average national discount rate from the rent-price ratio in 1985 using our model.

Our model also matches the increase in levels and dispersion of price–rent ratios if we assume that expected rent growth was 1 p.p. higher in the major agglomerations, keeping discount rates constant across cities, $r^A = r^B$. Given the small difference in observed rent growth and the stable return difference between major agglomerations and the national average, we assert that a constant difference in discount rates is more realistic than a constant difference in expected rent growth. A large-scale simulation of many different combinations of different model variables (Appendix 4.C) demonstrates that falling discount rates robustly lead to increasing housing price dispersion for most realistic value combinations for r and g.

From the rent-price ratios we observe in the data and assuming that expected rent growth is two percentage points in the superstars and on the national level, we can calculate the discount rates resulting from our model.

The resulting values are: $r^A_{1985} = 0.060$, $r^B_{1985} = 0.073$, $r^A_{2018} = 0.048$, $r^B_{2018} = 0.058$. This implies that the difference in discount rates between the superstars and the national average has even been falling slightly over time and is now equal to the long-run return difference we used for the calibration above. Regarding the size of the discount rates, estimates of ex-ante safe rates range from three to five percent for 1985 (Negro et al., 2019; Rachel and Summers, 2019) and estimates for the risk-premium on the equity market portfolio range between 2.5 and 4.3 percent for the period between 1950 and 2000 in the U.S. (Fama and French, 2002). This implies a discount rate on risky assets between 5 and 9 percent. The size of the national discount rate in 1985, therefore, seems credible. Lastly, the fall in discount rates predicted by the model is only around 1.5 percentage points, which is lower than the estimated decline in safe rates ranging from 3 to 5 percentage points (Negro et al., 2019; Rachel and Summers, 2019). This shows that it is not necessary to have a large fall in discount rates for our model to generate the increase in housing price dispersion over the increase in rent dispersion that we observe in the data. The difference in the fall in discount rates in our model and the estimated fall in safe rates can potentially be explained by two observations: First, Kuvshinov and Zimmermann (2020) argue that risk-premia on risky assets have increased between 1985 and 2015, partially offsetting the fall in safe rates. Second, observed average rent growth in the data has decreased for the last three decades relative to the period between 1950 and 1990, which might have led to a decrease in expected rent growth g for the superstar and on the national level.

4.5 Conclusion

In this paper, we present a novel explanation for increasing housing price dispersion that, unlike existing models, does not require a comparable rise in rent dispersion. The key new insight is that a uniform fall in real interest rates can have heterogeneous spatial effects. For realistic values for the fall in real discount rates, the model is able to reproduce the growing dispersion of price–rent ratios observed in the data even in the absence of changes in fundamentals. In light of the central role of rental and housing price dynamics in urban economics, more research is needed to integrate this mechanism into more complex spatial models.[14] An important takeaway of the paper is that increasing polarization of housing prices between "superstar cities" and the rest of the country is not just driven by supply-side restrictions, but that interest rates can play a central role not only for the pricing on a national level, but also for the growing dispersion of housing prices. For future research in urban economics this implies to also pay attention to financial factors when thinking about trends in regional housing markets. The findings of this paper potentially also speak to the housing market outlook in the current environment of rising interest rates. All else equal, some of the polarization of housing prices that we could observe over the past decades can be expected to revert if going forward real discount rates rise again.

14. A promising example of this is the dynamic spatial equilibrium model of housing demand and supply in Vanhapelto (2022).

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Appendix 4.A Superstar cities revisited

4.A.1 Rent growth

Gyourko, Mayer, and Sinai (2013) derive a set of propositions, that directly imply that superstar cities should have experienced stronger rent growth than the rest of the country. Proposition 1 states that superstar cities have higher rental values than the rest of the country. Proposition 3 states that an increase in aggregate income leads to stronger rental increases in the superstar cities than in the rest.[15] These two propositions are tested in Tables 2 and 3 of the paper, using log house value as the dependent variable. Here, we replicate the analysis focusing on the effects on house value growth and rent growth. Table 4.A.1 presents our regression output. There are two primary results. First, the coefficients for rent values are significant and positive, just as the coefficients for house values. Second, the coefficients for rent values are slightly less than half those of house values. This indicates that the effects on rents are much smaller than on prices, which raises the question of whether we can fully explain the strong divergence in prices with the divergence in rents.

Table 4.A.1. Replicating Panel A from Tables 2 and 3 in Gyourko, Mayer, and Sinai (2013)

	log house value	log rent value	log house value	log rent value
Superstar	0.605	0.291		
	(0.0729)	(0.0377)		
Superstar x Rich			0.394	0.172
			(0.0356)	(0.0193)
N	1116	1116	1116	1116
adj. R^2	0.414	0.308	0.856	0.861

Note: This table replicates Panel A from Tables 2 and 3 in Gyourko, Mayer, and Sinai (2013). In addition to the regression on log house value, we perform the same regression on rent log value. Columns 1 and 2 present the results of a regression of the left hand-side variable on a superstar dummy and year fixed effects. Columns 3 and 4 present the OLS coefficients of a regression on an interaction effect of a superstar dummy and the log number of rich families in the U.S. and time and superstar fixed effects. Standard errors are in parentheses and are clustered at the MSA-level.

4.A.2 Price-rent ratios

In this subsection, we present evidence that the divergence in price-rent ratios between superstar cities and the rest has strongly increased since the 1980s, extending the data set presented in Gyourko, Mayer, and Sinai (2013) to 2010 and

15. Propositions 2 and 4 relate to income growth in the superstar cities.

2018. We then use the definition of superstar cities to categorize the cities into superstars group and non-superstars groups, which we call the rest of the country. We estimate an equally weighted average of price–rent ratios for both groups by year. Figure 4.A.1 presents the results. The Figure shows that price–rent ratios have been increasing over time in superstar areas and in the rest of the country. However, in the superstar cities, price–rent ratios have increased much more, leading to a growing regional divergence in price–rent ratios.

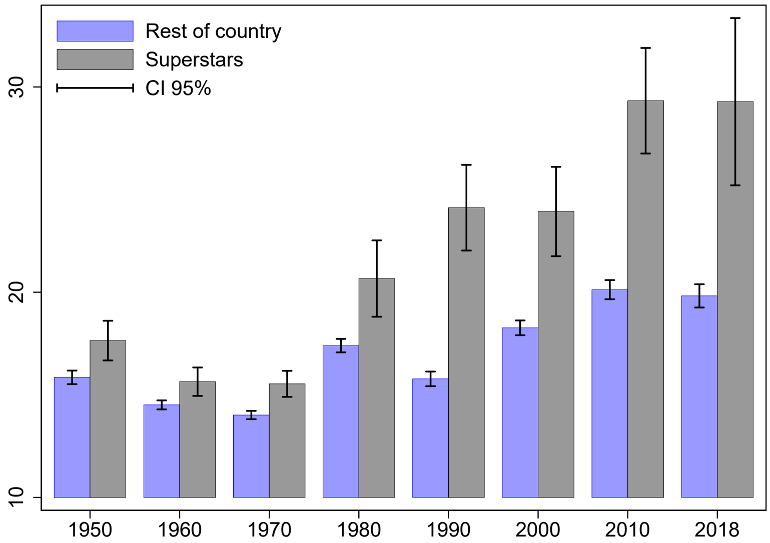


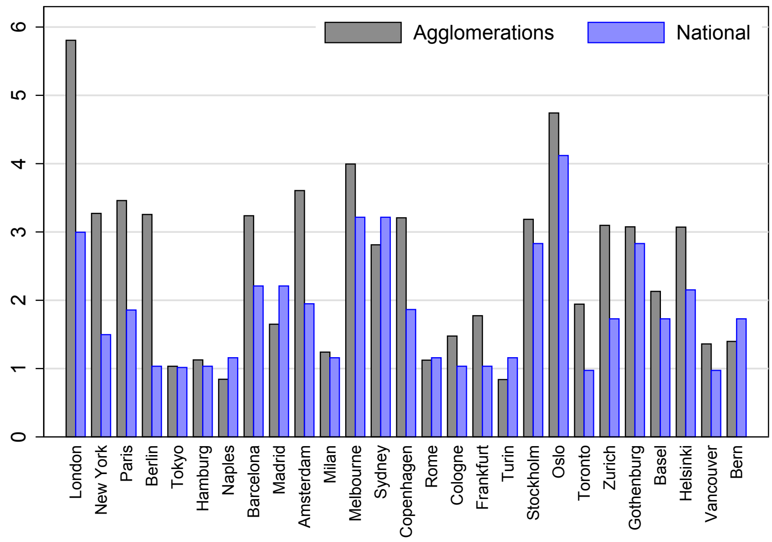
Figure 4.A.1. Price–rent ratios in the U.S., 1950-2018

Note: We define superstar cities as cities that were at least once a superstar city between 1950 and 2000 according to the superstar definition in Gyourko, Mayer, and Sinai (2013). We extended the data from Gyourko, Mayer, and Sinai (2013) to 2010 and 2018. Each bar represents an unweighted average by year for the specific group. 95% confidence bands are shown in black.

The model developed by Gyourko, Mayer, and Sinai (2013) predicts that price–rent ratios are higher in superstar cities, but it does not account for the growing gap between superstars and non-superstars over time.

Appendix 4.B Price and rent growth rates for 27 major agglomerations

(a) Housing prices



(b) Rents

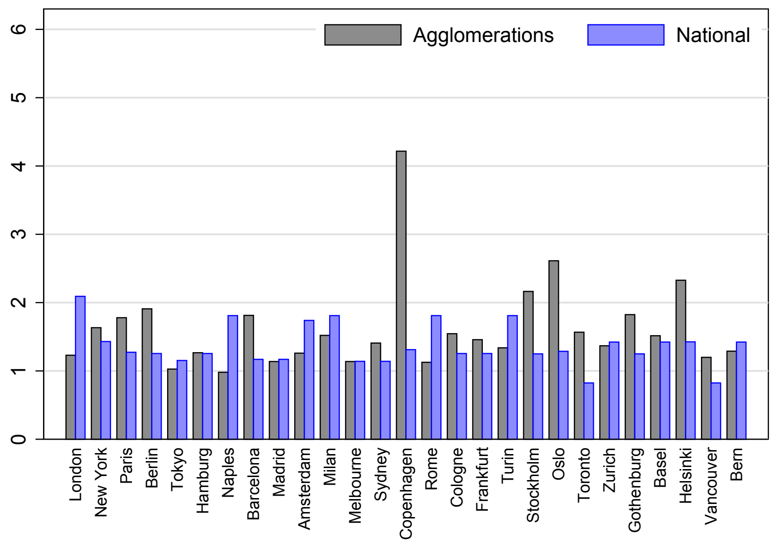


Figure 4.B.1. City-level growth rates for 27 major agglomerations compared to national averages

Note: Geometric mean of annual housing price (Panel (a)) and rent (Panel (b)) growth rates by city for 27 major agglomerations (black) and the respective national averages (blue).

Appendix 4.C Model simulation of risk–free rate fall on housing price divergence

To examine the scope conditions under which a falling discount rate leads to increasing housing price divergence between the agglomeration and the reservation city, we simulate our asset-pricing model for a range of potential, and not always realistic, values. The result displays the housing price divergence (in log) as a function of falling discount rates (in %) and is broken down for all possible combinations of differences in rent and discount rate growth rates between the agglomeration and reservation city (4.C.1). The figure demonstrates that housing price divergence occurs under a majority of calibrations, as long as the agglomeration rent growth excess and the reservation city excess discount rate is sufficiently high.

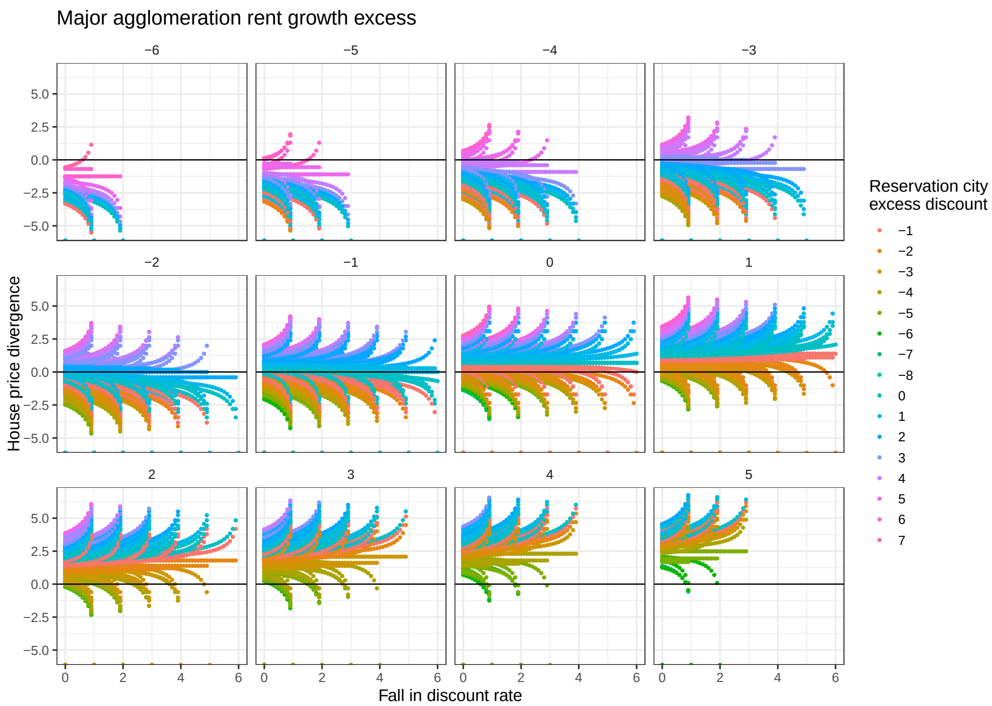


Figure 4.C.1. Simulation results by excess rent growth of agglomeration

Note: Facets show the percentage points by which the agglomeration's rent growth exceeds that of the reservation city. Colors indicate the percentage points by which the reservation city's discount rate exceeds that of the agglomeration.

Appendix 4.D Model evidence using U.S. MSA-level data

We also use the U.S. MSA-level data from Gyourko, Mayer, and Sinai (2013), which was extended to 2018 in Amaral et al. (2021), to test our mechanism empirically. We want to replicate Figure 3 in the main paper. Our mechanism predicts a one-to-one relation between rental yields in 1980 and in 2018, with a linear shift due to the fall in real discount rates (compare Figure 4.2 in the main paper). It also predicts a non-linear relation between rental yields in 1980 and price–rent ratios in 2018, with initially lower rental yield MSAs subsequently having disproportionately higher price–rent ratios (compare Figure 3 panel (b) in the main paper). As demonstrated below, these predictions hold to a great extent in the data.

Figure 4.D.1 panel (a) plots the rent–price ratios for all MSAs in 2018 relative to the rent–price ratios in 1980. It also shows a linear fit with the resulting regression coefficients. Rent–price ratios in 2018 can indeed be predicted by rent–price ratios in 1980 but have fallen uniformly by approximately 85 basis points. Of course, MSA-level rent–price ratios do not perfectly align with the regression line. This implies that rent–price ratios have also been affected by city–specific shocks. Not all variation in rent–price ratios can be explained by a fall in discount rates alone, however, the linear fit can explain approximately half of the variation in the data.

(a) Rent-price ratio 2018 **(b)** Price-rent ratio 2018

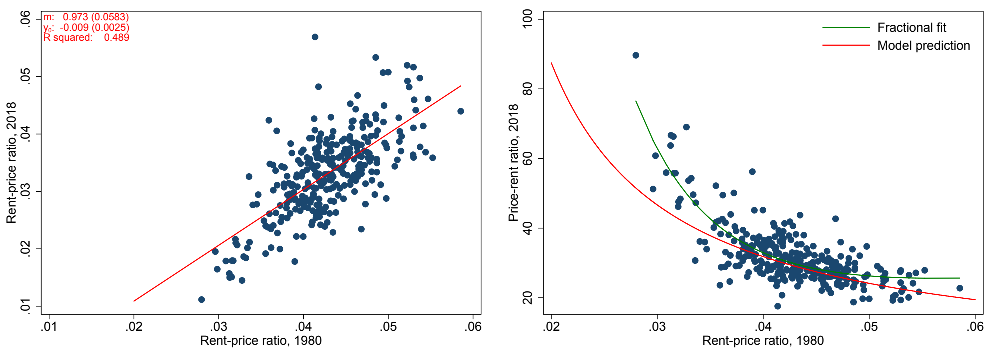


Figure 4.D.1. Comparison model and U.S. MSA-level data

Note: Panel (a) shows the rent–price ratios in 2018 relative to the rent–price ratios in 1980 together with a linear fit and the resulting regression coefficients (standard errors in parentheses). Panel (b) shows the price–rent ratio in 2018 relative to the rent–price ratio in 1980 together with a fractional fit and the predictions of our model resulting from the linear fit in Panel (a). The data is taken from Gyourko, Mayer, and Sinai (2013) and extended by Amaral et al. (2021).

Panel (b) of Figure 4.D.1 plots price–rent ratios in 2018, also presenting a fractional fit to the data (green line). The red line depicts the price–rent ratios that the model would predict for 2018, given the rent–price ratio in 1980 and the uniform fall in rent–price ratios estimated in panel (a). Again, the model does not fit the data perfectly, however, it does agree with the overall picture of the data and predicts higher price–rent ratios for cities that already had low rent–price ratios in 1980. The fact that price–rent ratios in cities with the lowest rental yields initially are even higher than predicted by the model leaves some room for alternative explanations. One example would be increasingly more optimistic rent expectations (g) in major agglomerations relative to the rest of the country. Another would be a tightening of supply constraints in major agglomerations.

Appendix 4.E Fall in real safe rates

Several papers have documented the long-run decline in real safe rates across OECD economies since the 1980s (Blanchard and Katz, 1992; Negro et al., 2019; Rachel and Summers, 2019). Using the estimates from Del Negro et al. (Replication data for: Global Trends in Interest Rates), we plot the time-series evolution of ex-ante real safe rates in the U.S. as well as averaged over 15 OECD economies in Figure 4.E.1. It is evident that real safe rates have been declining considerably both in the U.S. as well as across the world, since the 1980s.

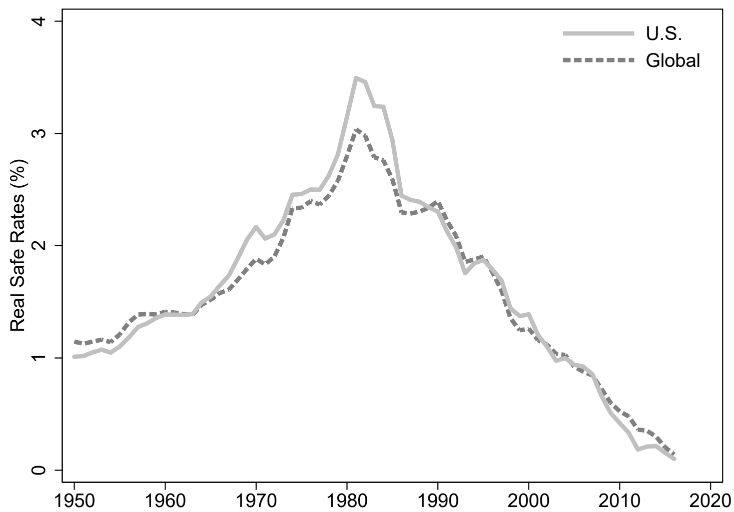


Figure 4.E.1. Global and U.S. Real Safe Rates, 1950-2016

Note: The Figure plots the posterior median of the trend in global and U.S. real safe rates. The estimates are taken from Negro et al. (2019).

Appendix 4.F USA Rent-price ratios 1980

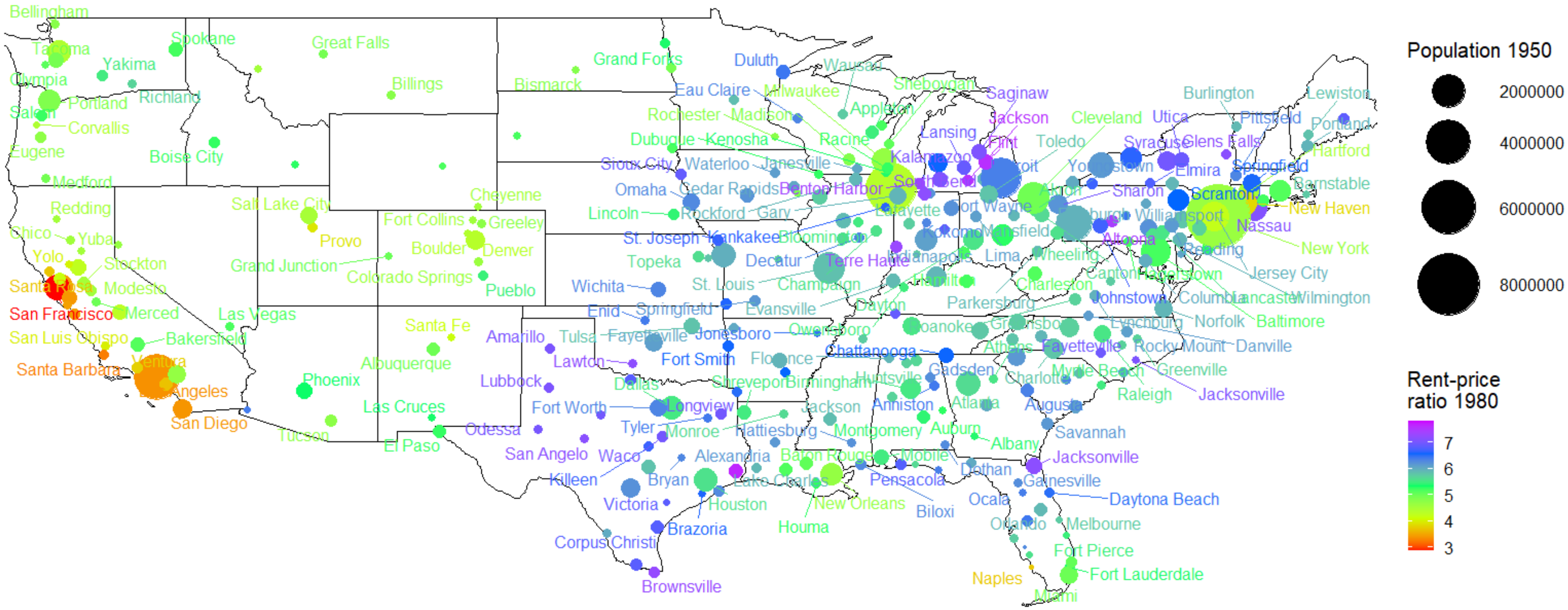


Figure 4.E.2. Rent–price ratios in the U.S. 1980

Note: Data for US MSAs are taken from Gyourko, Mayer, and Sinai (2013) extended for the period 2010 to 2018 with the American Community Survey.

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