Essays on Financial Intermediation and Financial Stability

Inauguraldissertation

zur Erlangung des Grades eines Doktors

der Wirtschafts- und Gesellschaftswissenschaften

durch die

Rechts- und Staatswissenschaftliche Fakultät

der Rheinischen Friedrich-Wilhelms-Universität Bonn

vorgelegt von

Simon Rother

aus Mainz

Bonn 2021

Dekan:	Prof. Dr. Jürgen von Hagen
Erstreferentin:	Prof. Dr. Isabel Schnabel
Zweitreferent:	Prof. Farzad Saidi, Ph.D.
Tag der mündlichen Prüfung:	16. Juli 2021

Acknowledgements

I am deeply grateful to the many people who have supported me on the journey to completing this dissertation. First and foremost, I would like to thank my advisors and, in the first two cases, co-authors Isabel Schnabel, Markus Brunnermeier, and Farzad Saidi. Isabel, much of my knowledge about being an economist has come from you. Among many other things, your intellectual rigor and your thoughtful voice in policy debates have been an inspiration. Despite your numerous obligations, you have always made time for me when it mattered. Thank you for your mentoring over the many years. Markus, our joint work and our conversations were both enlightening and inspiring for me. They have motivated me to aim higher and to look beyond easy answers. Thank you so much for the exchanges, for having me in Princeton, and for your invaluable support beyond that. Farzad, your guidance was always just a quick message away when needed and that has meant so much to me. I know you consider it part of your job, but you have definitely gone more than the extra mile. Thank you for becoming such an inspiring and reliable advisor.

I also owe a debt of gratitude to Hendrik Hakenes and many other people at the Bonn Graduate School of Economics, the Collaborative Research Center TR224, and the Cluster of Excellence ECONtribute, all of whom invest so much to provide the highly supportive and stimulating research environment that has been my academic home.

Furthermore, I wholeheartedly thank my numerous colleagues, some of whom I call friends today, who accompanied me throughout my Bachelor, Master, and PhD studies. I have learned so much from our countless discussions and the time we spent together has greatly contributed to making this journey a very enjoyable one. Special thanks go to my co-authors Oliver Rehbein and Christian Kubitza. Guys, thank you so much for everything. Also, I can't wait for our next road trip.

I am also indebted to my close friends. In the past years, we got to spend way too little time together, but our bonds feel as strong as ever. Thank you for remaining such an important part of my life. Lastly, I am eternally grateful to my parents, Cornelia and Jürgen, my sister, Sonja, and my partner, Sarah. We have shared so many joyous times but all of you have also always been by my side when times were grim. I cannot thank you enough. You mean the world to me.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Financial systems are a vital component of today's economies. They can, among others, reduce information asymmetries (Myers and Majluf, 1984), implement efficient monitoring (Diamond, 1984), and help to insure against, for instance, liquidity shocks (Diamond and Dybvig, 1983). As a result, financial systems can improve capital allocations (Wurgler, 2000) and support economic growth (Levine, 2005). However, financial systems are inherently prone to instability (Minsky, 1982), frequently suffer costly financial crises (Laeven and Valencia, 2018), and the financial sector can cause inefficient human capital allocations (Philippon and Reshef, 2012). Therefore, it is important to understand how the financial system allocates resources, why financial crises occur, and how regulation can support financial stability.

Focusing on one of the main actors within financial systems, banks, this thesis analyzes key determinants of financial intermediation and financial stability in three self-contained chapters. Chapter 2 – joint work with Oliver Rehbein – explores banks' lending behavior by analyzing the social ties within a society as an information channel in bank lending. It reveals that social connectedness increases lending, constitutes an information channel that benefits banks and the real economy, and partly explains the effects of physical distance. Thereby, the analysis complements two strands of literature that examine the lending barriers posed by distances and the efficiency of lending between peers. Turning to financial stability, Chapter 3 – joint work with Markus Brunnermeier and Isabel Schnabel – focuses on asset price bubbles, a primary source of financial fragility throughout history. It shows that the increase in financial fragility during asset price bubbles strongly differs across bank and also across bubble characteristics. The analysis yields several policy implications and adds a bank-level perspective to the macro-finance literature on asset price bubbles and financial crises. Lastly, Chapter 4 focuses on macroprudential regulation, one of the past decade's main regulatory innovations aimed at supporting financial stability. It supplements the literature, which reveals a wide array of channels through which this regulation has beneficial and detrimental effects, with an assessment of the overall consequences of macroprudential regulation for systemic financial stability. The results show that macroprudential tools can benefit financial stability, but they also call for supranational coordination of macroprudential regulation. Subsequently, I provide a more detailed overview of each chapter.

The analysis of the role of social networks in bank lending (Chapter 2) draws motivation from two observations. First, when people interact with each other, they naturally exchange information. As information travels along social ties, the geographic structure of real-world social networks may affect the availability of soft information across regions. Second, in bank lending, information frictions are particularly severe and banks' ability to efficiently overcome these frictions provides a key justification for the existence of these very institutions (Diamond, 1984; Boot, 2000). Together, these two points suggest that real-world social networks might facilitate banks' access to information, thereby improving lending decisions. Previous literature, however, has shown that direct social ties between bank managers and borrowers can result in inefficient loan allocations and impaired loan performances due to misaligned private incentives (Khwaja and Mian, 2005; Haselmann, Schoenherr, and Vig, 2018). Moreover, word-of-mouth information is not always reliable so that, overall, it is unclear whether and how real-world social networks might affect bank lending.

To explore these points, we exploit a unique dataset on Facebook friendship links that reflect social ties within the U. S. population. This allows us to analyze for the first time how the ubiquitous social network – that spans an entire society – affects banks' lending decisions. Specifically, we ask three questions. First, how does social connectedness affect the allocation of loans? Second, is this effect related to an information channel? And third, what are the consequences for banks and borrowers? Throughout the analysis, we account for physical and cultural distances, which aggravate information frictions (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Giannetti and Yafeh, 2012; Fisman, Paravisini, and Vig, 2017), thereby offering new insights into the role of these prominent lending barriers.

We find that banks from one county lend more to borrowers in another county if the people who live in these two counties are more socially connected. This effect of social connectedness is sufficiently large to compensate for the lending barriers posed by distances and partly explains the effect of physical distance. Social connectedness increases lending particularly strongly if lending requires more information and if banks have intact screening incentives. At the same time, social connectedness does not result in lending to riskier borrowers but is associated with lower borrowing costs and improved loan performances. Counties with a higher social proximity to banks exhibit, also at an aggregate level, more lending, higher GDP growth, and more employment, especially through small firms. The results thus unveil the important role of social connectedness in bank lending, which constitutes an information channel that benefits banks and the real economy.

Focusing on financial stability, Chapter 3 analyzes asset price bubbles, a primary source of fragility in the financial system throughout history. Indeed, some bubble episodes, such as the one preceding the global financial crisis, have devastating effects on the financial system. Yet, others, such as the dotcom bubble, pass without wider macroeconomic consequences. A key mechanism determining the severity of outcomes is the amplification of the shock of a bursting asset price bubble within the financial system, which oftentimes can be attributed to a small number of banks. While the impact of aggregate credit booms and asset price bubbles on macroeconomic outcomes such as financial crises is well documented (Jordà, Schularick, and Taylor, 2013, 2015a, 2015b), little is known about the role of individual financial institutions in the buildup of systemic risk during asset price bubbles.

This chapter fills this gap in the literature by analyzing the relationship between asset price bubbles and systemic risk at bank level. To this end, we employ two complementary bank-level measures of systemic risk and several methods to identify asset price bubbles in stock and real estate markets in 17 countries over almost 30 years.[1] Measuring systemic risk at bank level allows us to analyze changes in systemic risk across banks during asset price

[1]Specifically, we apply the BSADF test (Phillips, Shi, and Yu, 2015a, 2015b) and a trend-deviation approach (Jordà, Schularick, and Taylor, 2015b) to identify bubble episodes. The measures of systemic risk are ΔCoVaR (Adrian and Brunnermeier, 2016) and the marginal expected shortfall (MES) (Acharya et al., 2017).

bubbles and, thereby, yields information on which banks deserve increased regulatory attention as they exhibit particularly strong increases in systemic risk during bubble episodes. Moreover, the continuous measures also account for episodes of financial fragility that did not result in a crisis and they raise the statistical power of our estimates, which is important as banking crises and asset price bubbles are rare events.

The main results, which are robust across measures, show that systemic risk increases already during the boom phase of a bubble episode and even more so during its bust. Importantly, the size of this increase depends on bubble and, more strongly, on bank characteristics. Higher loan growth, a stronger maturity mismatch, and especially larger bank size tend to make financial institutions more vulnerable to asset price bubbles. Only in real estate booms, systemic risk of small banks increases relative to that of large banks, which is in line with the stronger focus on mortgage lending on the part of the former. In addition to emphasizing these heterogeneities, the results suggest several policy implications, among others, that policies at macroeconomic level alone are an insufficient response to asset price bubbles and, as longer boom phases and larger price bubbles are associated with larger increases in systemic risk, that it is advisable to counteract asset price bubbles early on.

Instead of a primary source of financial fragility, Chapter 4 focuses on macroprudential regulation, one of the main regulatory innovations during the past decade that aims to improve systemic financial stability. Macroprudential tools indeed successfully influence the measures that they directly target, such as credit and house price growth (Jiménez et al., 2017; Richter, Schularick, and Shim, 2019). However, they also create market frictions and induce regulatory arbitrage (Aiyar, Calomiris, and Wieladek, 2014; Jiménez et al., 2017), which shifts risks in potentially destabilizing ways and questions the overall effectiveness of the regulation. While the literature is insightful regarding channels and partial effects of macroprudential tools, little is known about the overall consequences of macroprudential regulation for systemic financial stability, which is particularly troublesome as the regulation has direct costs for the real economy (Richter, Schularick, and Shim, 2019).

To fill this gap, this chapter analyzes the effect of macroprudential regulation on systemic risk.[2] The analysis covers a broad array of macroprudential tools in more than 70 countries,

[2]The analysis exploits the dataset on macroprudential regulation introduced by Cerutti, Claessens, and Laeven (2017) and measures systemic risk based on MES (Acharya et al., 2017) and ΔCoVaR (Adrian and Brunnermeier, 2016).

which allows for an assessment as to which types of tools achieve most for financial stability and under what circumstances. The chapter also takes a cross-country perspective to analyze cross-border spillovers of macroprudential regulation and the complementarity between regulation at home and abroad. The employed systemic risk measures facilitate estimating the overall consequences of macroprudential regulation for financial stability, simultaneously allowing for beneficial and detrimental channels. The continuous nature of these measures is beneficial as financial crises are rare events, the time that has passed since the introduction of macropruential tools is limited, and the tools may affect systemic risk already well before a crisis. To address the reverse-causality concern that regulation usually reacts to financial fragility, I exploit that politicians appear hesitant to apply macroprudential tools, worrying that they antagonize voters who find it more difficult to obtain loans in case of tighter regulation. Specifically, I employ two instrumental variables based on heterogeneities in politicians' power to decide about the application of macroprudential tools, an idea introduced in Gadatsch, Mann, and Schnabel (2018), and, as macroprudential regulation varies with the political cycle (Müller, 2019), the distance to the next major election.

I find that macroprudential regulation reduces systemic risk, especially in developed, financially interconnected countries, and when bank-based tools are applied. From a cross-country perspective, macroprudential regulation at home and abroad complement each other: If their financial systems are sufficiently interconnected, tighter regulation in a home country reduces its systemic risk exposure to other countries, especially when regulation abroad is strict and, hence, the scope for regulatory arbitrage limited. Macroprudential regulation abroad also reduces home countries' systemic risk exposure, but to a lesser extent. The results emphasize that, overall, macroprudential regulation benefits financial stability such that regulatory arbitrage and the shifting of risks can serve as motivation for a careful use of macroprudential tools, but not as an argument against macroprudential regulation itself. Moreover, the findings call for supranational coordination to limit regulatory arbitrage across borders and, thereby, increase the effectiveness of the regulation.

Overall, the results in this thesis introduce the geographic structure of social ties as a new important determinant of bank lending, emphasize that the evolution of systemic risk during asset price bubbles strongly differs across banks, and provide evidence that macroprudential regulation benefits financial stability despite regulatory arbitrage.

Chapter 2

The Role of Social Networks in Bank Lending*

Abstract: This chapter analyzes social connectedness as an information channel in bank lending using Facebook data that reflect social ties within the U.S. population. After accounting for physical and cultural distances, social connectedness increases cross-county lending, especially when lending requires more information and screening incentives are intact. On average, a standard-deviation increase in social connectedness increases cross-county lending by 24.5%, which offsets the lending barrier posed by 600 miles between borrower and lender. County-level GDP growth and employment increase with social proximity. While the ex-ante risk of loans is unrelated to social connectedness, defaulting borrowers from well-connected counties cause smaller losses.

2.1 Introduction

Serving as an information channel, real-world social networks can help to overcome information frictions and, where they do, improve economic outcomes. In bank lending, the information frictions between borrower and lender are particularly important. They are costly to overcome and provide a key justification for the very existence of banks (Diamond, 1984; Boot, 2000). As soft information enters banks' lending decisions, strong social ties appear likely to result in a more efficient credit intermediation process by reducing the need

*This chapter is based on a paper co-authored with Oliver Rehbein. We thank René Bernard, Martin Brown, Hans Degryse, Ralph De Haas, Florian Heider, Mikael Homanen, Luc Laeven, Yueran Ma, Ralf Meisenzahl, Alexandra Niessen-Ruenzi, Steven Ongena, Loriana Pelizzon, Farzad Saidi, Martin Schmalz, Isabel Schnabel, Sascha Steffen, Johannes Stroebel, and seminar participants in Bonn and Zurich for valuable comments and suggestions. We also thank participants of the annual meeting of the German Finance Association (DGF) in Essen, the SAFE workshop on Household Finance in Frankfurt, the conference of the International Banking, Economics, and Finance Association (IBEFA) in San Diego, and the workshop on Banking in Mannheim for valuable feedback. Financial support from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (Projects C03 and C04) and through EXC 2126/1-390838866 under Germany's Excellence Strategy is gratefully acknowledged.

for and the cost of information acquisition about borrowers or their local economic environments. Yet, in the context of bank lending, social networks are predominantly associated with negative consequences such as inefficient loan allocations and impaired loan performance (Khwaja and Mian, 2005; Haselmann, Schoenherr, and Vig, 2018). These negative consequences result from crony lending between peers in exclusive networks. While it is important to be aware of this dark side of social ties, it remains unclear whether social networks, when defined more broadly, can facilitate banks' access to information and, thereby, improve bank lending. This question is of particular interest as social networks become increasingly widespread and people exchange information ever more rapidly.

We exploit a unique dataset that reflects social ties within the U.S. population. Based on this dataset, we analyze the role of social connectedness as an information channel in bank lending. Specifically, we ask three questions. First, how does social connectedness affect the allocation of loans? Second, is this effect associated with an information channel? And third, what are the consequences of these lending decisions for borrowers and banks? Our results suggest that social connectedness increases lending in a way that is in line with an information channel which benefits borrowers and banks. To account for prominent factors which aggravate information frictions, we control for the physical and cultural distances between borrower and lender throughout the analyses.

As such, this paper also offers new insights into the role of physical distance (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010) and cultural differences (Giannetti and Yafeh, 2012; Fisman, Paravisini, and Vig, 2017) in bank lending. We make use of the social connectedness channel to analyze to what extent the effect of physical distance can be attributed to soft information rather than to transportation costs. Information flows through social networks also offer a rationale for banks' limited ability to collect soft information at large distances, as the density of networks decreases with distance. Additionally, we study whether social connectedness can compensate for the lending barriers posed by physical and cultural distance and analyze the interactions of the effects of connectedness and distances.

To measure social connectedness, we leverage a recent dataset on Facebook friendship links in the United States (Bailey et al., 2018a), where the use of Facebook is pervasive. As of 2019, the share of monthly active users amounts to 75% of the total U.S. population. Facebook friendship links mostly correspond to real-world networks of relatives, colleagues, business partners, and friends. In 2020, COVID-19 infections spread along the social ties reflected by the data (Kuchler, Russel, and Stroebel, 2020). Hence, the data allow a comprehensive assessment of real-world social connections in which information can be exchanged both online and in person. The data are aggregated at the county-pair level and provide the relative probability of a person in county A being acquainted with a person in county B.

We supplement this information with data on loans to small and medium-sized enterprises (SMEs) from the Community Reinvestment Act (CRA) as well as mortgage lending from the Home Mortgage Disclosure Act (HMDA). Small firms tend to be more opaque borrowers for whom soft information is more important during the credit intermediation process. The mortgage-loan data also allow us to analyze the riskiness and the performance of loans. Our measure of cultural distance builds on the theoretical models of regional subcultures in Elazar (1984) and Lieske (1993). These models define culture as a combination of a person's ethnic ancestry, religious beliefs, racial origin, and the structure of their social environment. We collect a wide array of variables on these categories to compute the cultural distance between U.S. counties. The resulting measure is theory based, considers several dimensions of cultural identity, and corresponds to well-known patterns.

Our results reveal that social connectedness significantly increases county-to-county lending. In our baseline regression, a standard-deviation increase in social connectedness is associated with a 24.5% increase in SME loan volumes. For mortgage lending to households, we find a weaker effect, which is in line with an information channel, as the credit intermediation process is more standardized for mortgage loans and SMEs are more opaque borrowers. Social connectedness also increases the probability of bank lending from a source to a destination county. The effect of social connectedness is distinct from physical and cultural distances, for which we control in all regressions.

Interestingly, social connectedness explains part of the effect of physical distance. In line with the literature, loan volumes decrease with physical distance. However, accounting for social connectedness significantly shrinks this effect. The information that runs through social networks thus provides an explanation for the large distance effects in the literature. In economic terms, the opposing effects of social connectedness and physical distance are similarly large. A standard-deviation increase in social connectedness compensates for more than 600 miles of additional distance between borrower and lender. Hence, social connectedness can significantly help to overcome the lending barriers posed by physical distance. Similar to physical distance, cultural distance is also associated with lower loan volumes. However, this negative effect of cultural differences entirely disappears in the presence of sufficiently close social ties.

The relevance of social connectedness increases with banks' need for information. Small banks, which have a less standardized credit intermediation process, experience a larger increase of loan volumes in social connectedness. Similarly, social connectedness is more important when borrowers' creditworthiness is more challenging to evaluate because of a higher exposure to industry volatility or their local economic environments exhibiting a strong boom or bust. The relevance of social connectedness also increases if the local economic development in a borrower's region is very different from that in the bank's region, which constitutes an additional case of high information need. Conversely, social connectedness increases cross-county lending less for loans with reduced screening incentives due to government guarantees or securitization. These findings strongly suggest that social connectedness affects loan allocations because of an information channel.

Based on a loan-level analysis, we find no evidence of social connectedness being associated with more risky lending. Borrower credit scores and loan-to-value ratios are not significantly related to social connectedness. Borrowers from well-connected counties pay lower interest rates, which is in line with a lower cost of information acquisition for banks. While delinquency rates do not significantly vary with social connectedness, actual defaults lead to lower losses: controlling for the initial loan amount and further characteristics, a standard-deviation increase in social connectedness reduces the outstanding amount of defaulting loans by 80%. Banks thus profit from better performance of loans to borrowers from well-connected regions, which further supports the notion that social connectedness facilitates banks' access to information.

From the borrowers' perspective, social proximity to bank capital is highly valuable. In addition to more lending, counties with higher social proximity to bank capital experience higher GDP growth and more employment. Specifically, one standard deviation higher social connectedness is associated with 0.85 percentage points higher GDP growth and 0.5% higher employment. Regions with a high percentage of small firms, which rely more on bank loans for financing, profit particularly strongly from their social proximity to banks. The analysis of real effects thus provides no evidence of a connectedness-driven financing of negative net-present-value (NPV) projects.

Our baseline results on loan allocations rely on cross-sectional regressions using fixed effects to account for source-county and destination-county characteristics. We also control for a number of county-pair-specific variables which may influence county-to-county lending, including migration, commuting behavior, and trade. To improve identification, we construct a panel dataset to account for source-county-time and destination-county-time fixed effects, and estimate instrumental-variable regressions that exploit historical travel costs and the quasi-random rollout of Facebook as instruments. The estimates further corroborate our results on social connectedness. Moreover, our results are robust to alternative measures of physical and cultural distance, which emphasizes that the role of social connectedness in bank lending is distinct from these distances. The results cannot be explained by differences in state-level regulation either, as they apply within and across states. Lastly, the results are robust to alternative approaches to the clustering of standard errors, including dyadic clustering.

Overall, social connectedness increases bank lending, especially when banks have a high need for information and screening incentives are intact. Banks and especially borrowers profit from the resulting loan allocations. Hence, social networks, when defined broadly, can help to overcome information frictions and improve bank lending. These findings suggest three implications. First, regulators may want to take social connections into account in antitrust decisions. Whereas distance remains an important factor, a high concentration of lenders in a geographical area appears less problematic if it has close social ties to regions in which other banks are located. Second, social connectedness may help to explain the trend toward geographically more dispersed banks over the past decade. Social networks drive loan allocations and the networks have become increasingly widespread with an ever more rapid exchange of information. Third, banks may expand into a region more efficiently when strategically employing well-connected loan officers. While the literature shows that direct bonds between the borrower and lender lead to inefficient lending decisions, social ties to a borrower's region facilitate a bank's access to information and, on average, result in more efficient loan allocations.

Our paper is embedded in a broad literature on the importance of social networks for economic outcomes.[1] Jackson (2011) provides a comprehensive overview. Social networks are known to affect the quality of information flows and trust (Granovetter, 2005), thereby shaping economic outcomes. Several studies analyze how investment behavior depends on social connections.[2] Yet, despite banks actively relying on soft information for their lending decisions (Uchida, Udell, and Yamori, 2012; Liberti, 2018; Gropp and Güttler, 2018), and despite particularly pronounced information frictions between borrowers and lenders, the relevance of social connections as an information channel for bank-lending decisions has hardly been analyzed. La Porta, López de Silanes, and Shleifer (2002) and Khwaja and Mian (2005) show that political connections drive lending decisions. Haselmann, Schoenherr, and Vig (2018) show that bank directors extend more inefficient credit to members of their elite social club.[3] We contribute to this literature by analyzing the ubiquitous social network that spans a society rather than an elite club. Through this broad network, loan officers can receive information about a borrower or their local economic environment without having a direct personal connection to that borrower and, hence, without necessarily receiving a private benefit from crony lending. In line with this difference in the nature of the network, we find that social connectedness increases lending because of an information channel and in a way that is beneficial for banks and the real economy.

Furthermore, our paper relates to the literature on relationship banking (see, for example, Boot, 2000; Kysucky and Norden, 2016) in general and on the effects of physical distance in particular. The effect of physical distance on lending outcomes is highlighted by a long

[1] For instance, Duflo and Saez (2003) analyze the role of social networks in individual retirement decisions. Also see Ioannides and Datcher Loury's (2004) discussion of the role of social networks in labor markets. Nguyen (2012) and Kramarz and Thesmar (2013) look at social networks within boards and in the upper management of firms. Chaney (2014) and Bailey et al. (2021) investigate the role of networks in international trade. Bailey et al. (2018b) demonstrate that information about house price developments spreads along socially connected individuals. Bailey et al. (2019) study the role of social networks for the adoption of new products.

[2] See Kelly and Ó Gráda (2000), Hong, Kubik, and Stein (2004), Hong, Kubik, and Stein (2005), Ivković and Weisbenner (2007), Brown et al. (2008), Han and Yang (2013), Halim, Riyanto, and Roy (2019). Cohen, Frazzini, and Malloy (2008, 2010) demonstrate that mutual fund managers invest more frequently in firms to which they have social ties, which helps them to outperform the market. Kuchler et al. (2020) show that institutional investors invest more in firms located in areas to which they are well connected, but these investors do not achieve superior returns.

[3] Lin, Prabhala, and Viswanathan (2013) analyze data from a peer-to-peer lending platform and show that lenders' decisions depend on the behavior of a borrower's online friends.

list of influential studies.[4] While transportation costs are one potential explanation for the relevance of physical distance, parts of the literature explicitly rationalize the physical distance effects with banks being only able to collect soft information locally (see, for example, Agarwal and Hauswald, 2010).[5] Given the recent advances in information technology, the collection of soft information may be hindered more by differences in social and cultural backgrounds than physical transportation costs. We contribute to this literature by showing that the information flowing along social ties partly explains the large effects of physical distance and that social connectedness can compensate for the lending barrier posed by distance. These findings also speak to competition policies. Markets are often defined geographically, such that physical distance is a main driver of competition (Degryse and Ongena, 2005; Granja, Leuz, and Rajan, 2018), but our results illustrate that sociocultural factors also determine loan allocations.

Lastly, our paper connects to studies of cultural differences between borrowers and lenders. Beck et al. (2018) highlight that foreign banks have disadvantages in collecting local information, which may be due to cultural differences. From a firm's perspective, such disadvantages can be reduced by owning more foreign assets (Houston, Itzkowitz, and Naranjo, 2017). Giannetti and Yafeh (2012) demonstrate that cultural differences between countries affect cross-country lending. Based on data from India, Fisman, Paravisini, and Vig (2017) show that more loans are extended and repayment rates increase if the loan officer and the lender are similar in terms of caste and religion, which suggests that cultural differences aggravate information frictions in bank lending. Our findings are in line with these studies in that cultural distance constitutes a lending barrier. We contribute to this literature in two regards. First, we introduce a new measure of cultural differences between counties in the United States. This measure is theory-based, considers several dimensions of cultural identity, and corresponds to well-known patterns. Second, we analyze the interplay between social connectedness and cultural differences: cultural distance constitutes a lending barrier even when controlling for social connectedness, but the negative effects of cultural distance disappear in the case of sufficiently close social ties.

[4]The non-exhaustive list includes Petersen and Rajan (2002), Berger et al. (2005), Degryse and Ongena (2005), Brevoort and Hannan (2006), Mian (2006), DeYoung, Glennon, and Nigro (2008), Agarwal and Hauswald (2010), Hollander and Verriest (2016), Beck, Ongena, and Şendeniz-Yüncü (2019), Nguyen (2019).

[5]Also highlighting the relevance of information for lending distances, Degryse, Laeven, and Ongena (2009) find that banks with inferior information technology lend at shorter distances.

2.2 Empirical strategy

We conduct our analysis in three steps. First, we analyze how social connectedness affects the allocation of bank lending and how this effect depends on the information sensitivity of loans. Second, we further explore the information channel and assess consequences of the altered loan allocations based on a loan-level analysis of the ex-ante lending risk and the ex-post loan performance. Third, we analyze consequences for borrowers by studying the real effects of counties' social proximity to bank capital. Subsequently, we describe our empirical strategy in detail. The data are described in Section 2.3.

2.2.1 Allocation of bank lending

Baseline specification Our main variable of interest measures the strength of social connections between U.S. counties. In our baseline regressions, we explain bank lending from branches in source county i to borrowers in destination county j by the counties' social connectedness while controlling for their physical distance (in logs), their cultural distance, further county-pair-specific control variables, and source and destination county fixed effects.

$$\begin{aligned}\text{bank lending}_{i,j} = {} & \beta_1 \cdot \text{social connectedness}_{i,j} \\ & + \gamma_1 \cdot \ln(\text{physical distance})_{i,j} + \gamma_2 \cdot \text{cultural distance}_{i,j} \\ & + \gamma_3 \cdot \text{county-pair-level controls}_{i,j} + \alpha_i + \alpha_j + \epsilon_{i,j} \end{aligned} \tag{2.1}$$

The dependent variable is the volume of loans (in logs). In additional regressions, we analyze the probability of a lending relationship. The county-pair-specific control variables account for the GDP growth and unemployment differentials (in absolute terms), gross trade and migration, the share of the commuting population, and same-state and common-border indicator variables. We include the unemployment rate and GDP growth differentials, because banks may take into account how different economic conditions are compared to their home market. The trade volumes account for the interconnectedness of industries. Migration and commuting may simultaneously affect bank lending and social connectedness. The same-state indicator accounts for regulation that may hinder banks in expanding their business across state borders. Standard errors are clustered at the source- and destination-county levels.[6] Even though it appears unlikely that a significant share of the social connections in the population emerges due to bank lending, we lag all explanatory variables by one year to mitigate reverse causality concerns.

Additional identification Since counties' connectedness and distances are time-invariant or at least highly persistent, our baseline regression is based on cross-sectional data. The results do, however, also hold up in a longer panel, where we include source-county-time and destination-county-time fixed effects to control, for instance, for the time-varying economic conditions in the source county and credit demand in the destination county. To provide additional identification for our cross-sectional baseline setting, we introduce several instrumental variable approaches in Section 2.4.1 based on historical travel costs and the quasi-random rollout of Facebook.

Information sensitivity To explore whether the effect of social connectedness is related to information, we analyze heterogeneities across the information sensitivity of loans. To this end, we interact social connectedness in our baseline specification (Equation 2.1) with measures of bank types, borrower types, the borrowers' local economic environments, and loan types. This allows us to assess how the effect of social connectedness depends on banks' need for information and their screening incentives.

2.2.2 Lending risk and loan performance

To further distinguish between crony lending and the information channel and to learn about the consequences of social connectedness affecting banks' lending decisions, we analyze the riskiness of loans from an ex-ante and an ex-post perspective based on a loan-level sample. To this end, we estimate loan-level regressions that explain the riskiness of loan l originated in year t by bank b by the social connectedness between source county i (=branch location) and destination county j (=borrower location) while controlling for physical and

[6] The results are robust to state-level and dyadic clustering (see Table 2.B.1 in the appendix).

cultural distance, additional loan characteristics, and bank and origination-year fixed effects.

$$
\begin{aligned}
\text{riskiness}_l = {} & \beta_1 \cdot \text{social connectedness}_{i,j} \\
& + \gamma_1 \cdot \ln(\text{physical distance})_{i,j} + \gamma_2 \cdot \text{cultural distance}_{i,j} \\
& + \gamma_3 \cdot \text{additional loan characteristics}_l + \alpha_b + \alpha_t + \epsilon_l
\end{aligned} \tag{2.2}
$$

Our measures of ex-ante riskiness are the borrower's credit score and the loan-to-value ratio. The ex-post loan performance is based on delinquency rates and the remaining outstanding amount of defaulting loans. We also analyze the relationship between social connectedness and the loans' interest rates. The additional loan characteristics control for the original loan amount (in logs), the debt-to-income ratio, and whether the borrower is a first-time home buyer.

2.2.3 Real effects

To assess implications of social connectedness from a borrower perspective, we estimate the real effects of borrower counties' social proximity to bank capital. Specifically, we regress an outcome in county c on the county's social proximity while controlling for its physical and cultural proximity, county- and state-time fixed effects, and additional control variables.

$$
\begin{aligned}
\text{outcome}_{c,t} = {} & \beta_1 \cdot \text{social proximity}_{c,t-1} \\
& + \gamma_1 \cdot \text{physical proximity}_{c,t-1} + \gamma_2 \cdot \text{cultural proximity}_{c,t-1} \\
& + \gamma_3 \cdot \text{additional control variables}_{c,t-1} + \alpha_c + \alpha_{s,t} + \epsilon_{c,t}
\end{aligned} \tag{2.3}
$$

The outcome variables are loan volumes (in logs), real GDP growth, and employment (in logs). The additional control variables account for industry shares, commuting, and migration. All explanatory variables enter the regressions lagged by one year.

2.3 Data

For our analyses, we construct three main datasets. First, to study loan allocations, we collect data on county-to-county lending, which corresponds to the level of observation of our main explanatory variable, social connectedness. Second, we build a loan-level sample to analyze the riskiness and performance of loans. Third, we construct a county-level sample to study real effects. Subsequently, we discuss each dataset in detail. Table 2.A.1 in the appendix summarizes the data sources and provides variable definitions.

2.3.1 Allocation of bank lending

Social connectedness Our measure of social connectedness is based on a 2016 cross section of the universe of Facebook friendship links from the United States, introduced by Bailey et al. (2018a). This dataset provides county-pair level information about the relative probability that a person in county i is acquainted with a person in county j. Specifically, social connectedness is defined as the number of cross-county Facebook friendship links divided by the product of county pair populations, scaled by an unknown factor for confidentiality reasons:

$$Social\ connectedness_{i,j} = \frac{Number\ of\ friendship\ links_{i,j}}{Population_i \cdot Population_j} \cdot Scaling\ factor \tag{2.4}$$

We winsorize the variable at the 99^{th} percentile to account for outliers in the distribution. Additionally, we divide the variable by the maximum social connectedness between any county pair so that the final variable can be interpreted as the social connectedness in percent of the maximum social connectedness between any two counties.[7] The measure reveals the structure of real-world social networks as the use of Facebook is pervasive across the U.S. population and Facebook friendship links predominantly correspond to real-world connections between relatives, friends, colleagues, and business partners (Bailey et al., 2018a), as was also illustrated by COVID-19 infections spreading along the social ties within the data (Kuchler, Russel, and Stroebel, 2020).

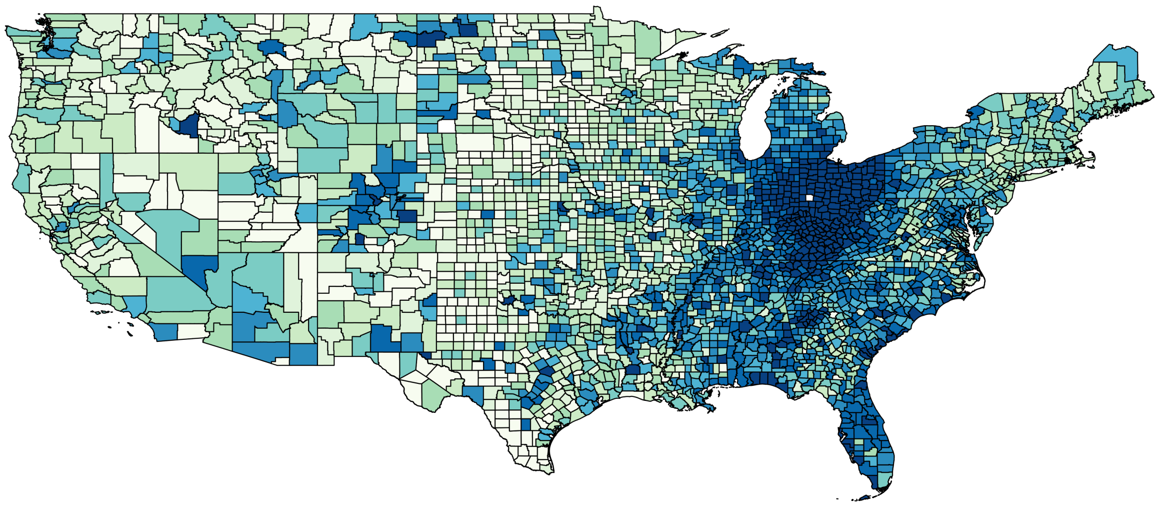
Figure 2.1 illustrates the variation in social connectedness based on the example of Montgomery County, OH, which is representative in our data in terms of its correlation with physical and cultural distances. The largest city in this county is Dayton. Areas colored in

[7] We find no evidence of a logarithmic relationship between cross-county loan volumes and the resulting measure of social connectedness. Moreover, our baseline results are robust to using the logarithm of social connectedness without previously winosrizing and rescaling the variable (compare Tables 2.4 and 2.B.2). Hence, our results cannot be explained by our winsorizing and rescaling of the social-connectedness variable.

dark blue exhibit the highest social connectedness, light colors represent low connectedness. Many counties in or near Ohio are socially well-connected to Montgomery County. However, there are also significant connections to more distant areas such as Southern Florida, parts of Colorado and the East Coast, and a number of individual counties scattered across the United States. The high connectedness to Southern Florida is in line with its status as a prime destination for retirement and tourism among people in the northeast of the United States. The close social ties to the various more scattered counties also correlate with a common factor: the largest employer in Montgomery County is the Wright-Patterson Air Force base and most of these closely connected counties also host Air Force bases. For example, the lone dark-blue spot in Idaho is Elmore County, which hosts the Mountain Home Air Force Base that accounts for 15% of the county's population.[8] While social connectedness and physical distance are significantly correlated (-0.49), the figure illustrates that counties within the same area can differ strongly in their social connectedness, which is partly determined by highly idiosyncratic county characteristics and allows us to estimate the effect of social connectedness while controlling for distance.

Figure 2.1: An example of a county's social connectedness

The figure displays the social connectedness between Montgomery County, Ohio, and all other U.S. counties. Dark-blue-colored areas exhibit the highest social connectedness, light-colored areas the lowest social connectedness. Montgomery County is represented by the white spot in the middle of the cluster of dark-blue counties. The county is representative of our sample in terms of the correlation between social connectedness, physical distance, and cultural distance.



[8]The non-exhaustive list of additional examples include the Minot Air Force Base in Ward County, North Dakota; the US Air Force Academy in El Paso County, Colorado; the Ellsworth Air Force Base in Pennington County, South Dakota; the Altus Air Force Base in Jackson County, Oklahoma; and the Creech and Nellis Air Force Bases in Clark County, Nevada.

Lending For our main analyses, we obtain data on lending to small and medium-sized enterprises collected under the Community Reinvestment Act (CRA). These firms are opaque borrowers, making soft information particularly important for banks. The dataset exhibits a broad coverage and comprises *newly originated* loans which amount to over 230 billion USD for 2017.[9] Additional regressions rely on mortgage-lending data collected under the Home Mortgage Disclosure Act (HMDA), which also indicates whether a loan is backed by government guarantees or sold for securitization. The mortgage-lending data comprise 14.3 million loans originated from 5,852 financial institutions in 2017.[10] Both datasets are available through the Federal Financial Institutions Examination Council (FFIEC). We assign each loan to the lending bank's branch located closest to the borrower based on branch locations provided by the FDIC.[11] Using the borrower locations reported in the datasets, we aggregate information on total loan volumes at the county-pair level.

Physical distance We obtain data on the great-circle distance between counties from the National Bureau of Economic Research's (NBER) county distance database. County locations are based on county centroids defined by the U.S. Census Bureau and usually correspond to a county's geographical center. In robustness checks, we consider the great-circle distance between population-weighted county centroids (U.S. Census Bureau) and traveling costs by highway, rail, and waterways (National Transportation Center).

Cultural distance We construct a measure of cultural distance at the U.S. county-pair level based on the theoretical models of regional subcultures in Elazar (1984) and Lieske (1993). These models characterize culture as an outcome of a person's ethnic ancestry, racial origin, religious beliefs, and the structure of their social environment. To operationalize the models, we collect 39 variables in these four categories from the 2010 U.S. Census, the 2010 American Community Survey, and the 2010 U.S. Religious Congregations and Membership Study. Table 2.A.2 in the appendix provides an overview of the variables in each category and, in the case of the social environment, subcategories. Figure 2.2 illustrates the variation in the data based on a cluster analysis of the principal components of the 39 culture variables. The

[9] For reporting requirements see `https://www.ffiec.gov/cra/reporter.htm`.

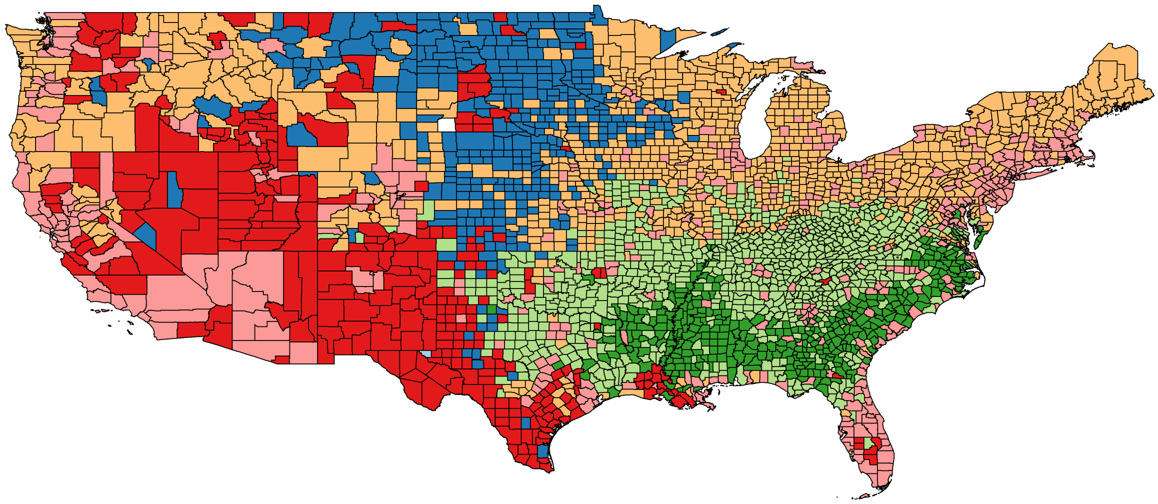
[10] Reporting requirements depend on a number of criteria such as balance sheet size and the number of mortgage loans. These criteria change on a yearly basis. For more information see `https://www.ffiec.gov/hmda/default.htm` or `https://www.consumerfinance.gov/data-research/hmda/learn-more`.

[11] For robustness, we alternatively determine source locations based on banks' headquarters. The findings are robust with slightly smaller estimates in economic terms (see Table 2.B.3 in the appendix), which is plausible as bank headquarters can always obtain information from their branches.

resulting pattern corresponds to well-known historical patterns such as the so-called Black Belt (dark green area) in the southeast of the United States.

Figure 2.2: Clusters of regional subcultures in the United States

The figure displays regional subcultures in the United States based on a cluster analysis of our culture data. For this analysis, we determine the principal components of our 39 individual culture variables. We keep the ten principal components with eigenvalues larger than 1 and sort counties into seven clusters by minimizing the mean of the Euclidean distance between the principal components' scores. The number of clusters is chosen based on an elbow method with 1,000 repetitions of randomly chosen starting counties for each cluster. The figure's pattern is robust to the number of principal components and clusters.



To measure the cultural distance between counties, we calculate the absolute difference per county pair for each variable and sum these differences across all variables of one subcategory. Afterward, we sum across subcategories and, finally, across categories. To ensure equal contribution to the variation within the final variable, within categories, and within subcategories, we normalize every summand to mean zero and variance one before calculating the sum. As we analyze in Section 2.5, our results are robust to including all 39 culture variables individually, but the aggregation allows for a meaningful interpretation of cultural differences.[12] We scale the final variable to range between 0 and 100 so that it can be interpreted as the cultural distance as a percentage of the maximum cultural distance between any two U.S. counties. As expected, cultural distance correlates negatively to social connectedness (-0.17) and positively to physical distance (0.38). When regressing social connectedness on physical and cultural distance, the distances explain 24% of the variation in

[12]We also exploit differences in voting patterns as a proxy for cultural differences, and account for the cultural heterogeneity within counties (see Section 2.5).

social connectedness, such that there is sufficient remaining variation to analyze the effects of social connectedness while controlling for physical and cultural distance.

Further main covariates We collect gross-commuting and gross-migration population shares at the county-pair level (U.S. Census Bureau), state-to-state gross trade volumes (Census Bureau Commodity Flow Survey), and two dummy variables indicating whether county pairs share a common border (U.S. Census Bureau) and whether they are located in the same state (NBER's county distance database). We also obtain data on counties' three-year average real GDP growth (Bureau of Economic Analysis) and unemployment rates (Bureau of Labor Statistics) and calculate the absolute value of the county-to-county difference for each of the two variables.

Final dataset Most of the over 9.5 million county pairs in the United States exhibit no cross-county lending. To avoid that the dependent variable mostly equals zero, we restrict our sample to county pairs with at least one cross-county loan. The lower number of observations also leaves us on the conservative side with respect to the statistical significance of our estimates. Our results hold in a dataset that includes all county pairs, which we also use to analyze the probability of lending between county pairs.

Our final dataset comprises lending to SMEs from 1,944 source counties in 50 states to 3,086 destination counties in 50 states, resulting in a total of 66,684 county pairs. Mortgage lending takes place between 34,483 county pairs, but only 8,532 county pairs simultaneously exhibit both types of lending. Subsequently, we discuss summary statistics for our main sample of SME lending (Table 2.1), but the variation in the mortgage-lending sample is similar (compare Table 2.B.4 in the appendix). The median volume of cross-county lending is close to 140,000 USD and the distribution is highly skewed as loan volumes can amount to almost 1.3 billion USD. The median social connectedness is only 2% of the maximum social connectedness between counties and social connectedness varies greatly, as the standard deviation equals 35. The median county-to-county distance is slightly above 400 miles. The median cultural distance equals 16% of the maximum cultural distance between counties. The GDP growth and unemployment differentials, gross trade, gross migration, and gross commuting show a large range, reflecting the variety of economic and structural conditions across regions in the United States.

Table 2.1: Descriptive statistics

The table displays descriptive statistics for the main sample used to analyze social connectedness and the allocation of bank lending. All variables are at the county-pair level. For instance, "volume of SME loans" equals the volume of loans provided by all bank branches in a source county to the small and medium-sized enterprises in a destination county. Table 2.A.1 in the appendix summarizes variable definitions and data sources. Tables 2.2, 2.3, and 2.B.4 report descriptive statistics for the additional samples used to analyze heterogeneities across the information sensitivity of loans in Section 2.4.1.2, the riskiness of loans in Section 2.4.2, and real effects in Section 2.4.3.

	N	Mean	Median	SD	Min	Max
Connectedness and distances						
Social connectedness	66,684	20	2	35	0	100
Cultural distance	66,684	17	16	7	0	72
Physical distance [miles]	66,684	578	413	566	4	4,996
log(Physical distance)	66,684	5.8	6.0	1.3	1.5	8.5
Lending data						
Volume of SME loans [thousand USD]	66,684	1,057	142	9,132	0	1,296,303
log(Volume of SME loans)	66,684	11.9	11.9	2.0	0.0	21.0
County-pair-level control variables						
Common border	66,684	0.1	0	0.3	0	1
GDP growth differential [ppt.]	66,684	3.6	2.7	3.4	0.0	46.9
Gross commuting [%]	66,684	0.1	0.0	0.6	0.0	16.9
Gross migration [%]	66,684	0.03	0.00	0.13	0.00	3.20
Gross trade [million USD]	66,684	85	38	114	0	814
Same state	66,684	0.2	0	0.4	0	1
Unemployment differential [ppt.]	66,684	1.5	1.1	1.4	0.0	21.4
Instrumental variables						
Historical travel costs	56,265	7	5	4	1	38
Relative Facebook county rank	57,105	0.04	0.02	0.05	0.00	0.48
Same highway	66,684	0.1	0	0.3	0	1
Years since highway construction	66,684	5	0	15	0	79
Further variables from interaction terms						
Bank size	66,684	17.3	17.5	2.1	0.0	21.5
Borrower's volatility exposure	66,684	2.4	2.2	0.9	0.5	9.3
GDP growth	66,684	1.8	1.5	4.0	-26.7	47.3

2.3.2 Lending risk and loan performance

Sample construction and additional data sources We merge the HMDA data with Fannie Mae's and Freddie Mac's Single Family Loan-Level Datasets, which contain detailed information on borrower characteristics, loan characteristics, and loan performance of 30-year fixed rate mortgages acquired by these two institutions. With the exception of the loan performance measures, all variables used in our analyses are as of the time of origination. The Single Family data and the HMDA data do not contain a unique identifier. We follow the strategy in Saadi (2020) to merge only uniquely identified sets of loans based on observable characteristics.[13] This restricts the sample to a representative subset of the Single Family datasets.

[13]Specifically, origination year, original loan amount, loan purpose, occupancy type, and three-digit ZIP code.

Final dataset and main additional variables Our final sample contains 20,760 loans originated between 2000 and 2008. We observe the performance of these loans until the end of 2018. Table 2.2 reports summary statistics. The distribution of the connectedness and distance variables, still based on the locations of the borrower and of the branch of the bank that originally originated the loan, is similar to our baseline sample of cross-county loans. Borrowers' FICO scores as of the origination date range between 300 and 835 and the median credit score is fair (638). At the median, a mortgage loan pays an interest rate of 6.4%, amounts to 150,000 USD, and finances 80% of the value of the purchased property. All three variables vary significantly. Ten percent of the loans are delinquent (90 days past due at least once), but only 0.8% of the loans have defaulted. The median outstanding amount at the time of default is 38,000 USD.

Table 2.2: Descriptive statistics: loan-level sample of borrower and loan characteristics

The table displays descriptive statistics for the loan-level sample used to analyze the relationship between social connectedness and the ex-ante and ex-post riskiness of loans. "Combined LTV" is the combined loan-to-value ratio of all mortgages on the borrower's property. "DTI" is the borrower's debt-to-income ratio. "FICO score" is a measure of the borrower's creditworthiness. "Delinquent" is a dummy variable which indicates mortgages that have been at least 90 days past due at least once. Table 2.A.1 provides variable definitions and data sources.

	N	Mean	Median	SD	Min	Max
Connectedness and distances						
Social connectedness	20,760	26	2	40	0	100
Cultural distance	20,760	16	16	7	1	44
Physical distance [miles]	20,760	551	420	521	3	4,152
log(Physical distance)	20,760	5.6	6.0	1.4	1.4	8.3
Ex-ante loan risk						
Combined LTV	20,760	82	80	15	5	120
DTI	20,760	35	35	12	2	65
FICO score	20,760	727	737	56	300	835
Loan characteristics						
First-time buyer	20,760	0.2	0	0.4	0	1
Interest rate [basis points]	20,760	648	638	83	425	1,075
Original loan amount [thousand USD]	20,760	161	150	88	6	802
log(Original loan amount)	20,760	4.9	5.0	0.6	1.8	6.7
Ex-post loan performance						
Delinquent	20,760	0.1	0	0.2	0	1
Not in default	20,760	0.992	1	0.1	0	1
Unpaid balance [thousand USD]	20,760	79.9	38	96.8	0	753
log(Unpaid balance)	20,760	-0.4	3.6	5.8	-6.9	6.6

2.3.3 Real effects

Proximity to bank capital To analyze real effects, we construct a dataset at the county level. We calculate a county's proximity to banks following the centrality measure of institutional investment in Kuchler et al. (2020). Specifically, we weight social connectedness with bank capital in each county:

$$\textit{Social proximity to bank capital}_{i,t} = \sum_j \textit{Social connectedness}_{i,j} \cdot \textit{Total bank assets}_{j,t}\,. \tag{2.5}$$

Similarly, we measure a county's physical and cultural proximities as

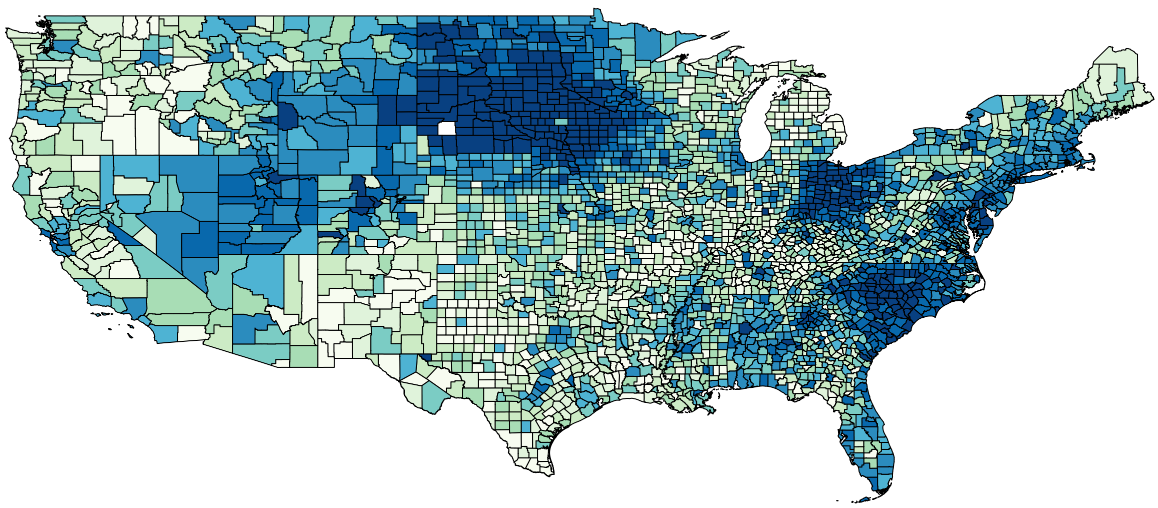
$$\textit{Physical proximity to bank capital}_{i,t} = \sum_j \textit{Phyiscal distance}^{-1}_{i,j} \cdot \textit{Total bank assets}_{j,t}\,.$$

$$\textit{Cultural proximity to bank capital}_{i,t} = \sum_j \textit{Cultural distance}^{-1}_{i,j} \cdot \textit{Total bank assets}_{j,t}\,. \tag{2.6}$$

Total bank assets is the sum of total assets of all banks with headquarters in county j, which we obtain from the FDIC. We standardize the variables to a standard deviation of 1 to ease the interpretation of our estimates. Figure 2.3 illustrates counties' social proximity to bank capital as an average over the years 2009 to 2017. Dark-blue areas mark counties with high social proximity, light colors represent low proximity. The figure clearly identifies main financial hubs such as New York, Charlotte, or Minneapolis and St. Paul, but again social proximity correlates only moderately with physical (0.18) and cultural proximities (0.26). Together, the two variables explain only 9% of the variation in social proximity, allowing us to analyze the effects of social proximity while controlling for locations and culture.

Figure 2.3: Counties' social proximity to bank capital

The figure illustrates each county's social proximity to bank capital. Dark-blue-colored areas exhibit the highest social proximity, light-colored areas the lowest social proximity. County i's social proximity to bank capital at time t is defined as $\sum_j \textit{Social connectedness}_{i,j} \cdot \textit{Total assets}_{j,t}$. The figure displays averages over the years 2009 to 2017.



Additional variables and final dataset We accompany the proximity measures with our data on county-level real GDP growth, lending to SMEs, commuting, and migration. Additionally, we obtain data on employment (U.S. Bureau of Labor Statistics), industry shares (U.S. Bureau of Economic Analyses), and the percentage of small firms (U.S. Census Bureau's Statistics of U.S. Businesses). Our final sample covers 3,021 counties over the years 2009 to 2017.

Table 2.3 reports summary statistics. Due to the standardization, the proximity measures have a standard deviation of 1, such that their coefficients reflect the change in a dependent variable that is associated with a standard-deviation increase in a proximity measure. As expected, loan volumes, which are now aggregated at county level and include within-county lending, are larger than in the cross-county setting. In line with more volatile economic developments at more disaggregate levels, the standard deviations of GDP growth and employment are large (7.6 and 152,467). The median share of small firms is 57%.

Table 2.3: Descriptive statistics: county-level sample for the analysis of real effects

The table displays descriptive statistics for the county-level analyses of the real effects of counties' social proximity to bank capital. For readability, we do not display summary statistics for the industry shares used as control variables. Table 2.A.1 provides variable definitions and data sources.

	N	Mean	Median	SD	Min	Max
Connectedness and distances						
Social proximity	24,161	1.1	0.7	1.0	0.1	8.3
Cultural proximity	24,161	4.5	4.4	1.0	1.2	9.2
Physical proximity	24,161	0.6	0.5	1.0	0.1	38.0
Dependent variables						
Employment	24,161	47,459	11,024	152,467	62	4,883,640
log(Employment)	24,161	9.5	9.3	1.5	4.1	15.4
Loan volume [thousand USD]	24,152	66,996	9,818	248,022	1	8,843,872
log(Loan volume)	24,152	16.2	16.1	1.9	6.9	22.9
Real GDP growth [%]	24,161	1.5	1.1	7.6	-20.1	33.3
Control variables						
Commuting from county	24,161	40,068	8,556	138,144	0	4,516,714
log(Commuting from county)	24,161	8.3	9.1	3.4	0.0	15.3
Commuting to county	24,161	39,903	7,167	149,760	0	4,665,782
log(Commuting to county)	24,161	8.1	8.9	3.4	0.0	15.4
Migration	24,161	6,128	1,604	15,324	1	289,585
log(Migration)	24,161	7.5	7.4	1.5	0.0	12.6
Small-firm share	24,161	57.3	56.8	12.4	8.2	100.0

2.4 Results

Our analysis proceeds in three steps. First, we analyze how social connectedness affects loan allocations. Second, we explore how social connectedness relates to the ex-ante lending risk and the ex-post loan performance. Third, we analyze the real effects of social proximity to banks.

2.4.1 Allocation of bank lending

To study how social connectedness affects loan allocations, we first explain cross-county loan volumes by social connectedness and analyze how this effect relates to physical and cultural distances. Afterward, we begin to explore the information channel and assess how the effect of social connectedness depends on the information sensitivity of loans.

2.4.1.1 Loan allocations in light of connectedness and distances

Baseline estimates We begin our main analysis by regressing cross-county loan volumes to small and medium-sized enterprises (in logs) on social connectedness, county-pair-specific control variables, and source and destination county fixed effects. Column 1 of Table 2.4 reports the results. Counties with higher social connectedness exhibit more cross-county lending. The coefficient of social connectedness indicates that an increase in social connectedness by one percentage point is associated with a statistically significant increase in lending of 1.2%. The next two columns of Table 2.4 repeat our previous regression but include physical distance (column 2) or cultural distance (column 3) instead of social connectedness. Both variables are significantly and negatively related to bank lending. In line with the literature, physical distance (e.g., Degryse and Ongena, 2005; Agarwal and Hauswald, 2010) and cultural distance (e.g., Giannetti and Yafeh, 2012; Fisman, Paravisini, and Vig, 2017) constitute lending barriers. In contrast, social connectedness increases bank lending.

The coefficients of the control variables have the expected signs (see Table 2.B.5 in the appendix). Loan volumes are higher within states and in neighboring counties. The GDP growth and unemployment differentials are associated with lower loan volumes, although the coefficients are not statistically significant. Lastly, loan volumes tend to increase with gross trade, commuting, and migration between the counties.

Column 4 of Table 2.4 reports the results for our baseline regression (see Equation 2.1), which simultaneously includes social connectedness and physical and cultural distance together with the control variables and fixed effects. The coefficient of social connectedness decreases but remains positive and statistically significant. Hence, bank lending increases with social connectedness and this relationship is distinct from physical and cultural distance. The coefficients of physical and cultural distance also become smaller (in absolute terms; see bottom part of Table 2.4) but remain statistically significant. The weakening relationship between bank lending and physical distance is mainly caused by including social connectedness.[14] Consequently, the physical distance effect in the literature can partly be explained by the structure of social ties and, as analyzed in more detail below, the information flowing along these ties. Transportation costs, on the other hand, may still play a role as bank lending significantly decreases with physical distance even when accounting for social connectedness and cultural distance. In Section 2.5, we exploit explicit measures of transportation costs and find additional support for the distinct relationship between loan allocations and social connectedness.

The increase in bank lending associated with closer social ties is sizable. As the standardized beta coefficients reported at the bottom of Table 2.4 illustrate, a standard-deviation increase in social connectedness is associated with an increase in loan volumes by 0.12 standard deviations. The standardized beta coefficients of physical distance and cultural distance equal -0.17 and -0.06, respectively. Hence, loan volumes increase with social connectedness twice as much as they decrease with cultural differences and almost as much as they decrease with physical distance. Put differently, at a median physical distance, a standard-deviation increase in social connectedness can compensate for the lending barriers of 621 additional miles between borrower and lender, which equals 1.5 times the median distance in our sample.[15] Overall, our baseline estimates reveal the important role of social

[14] Adding social connectedness to the specification in column 2 of Table 2.4 changes the coefficient of physical distance from -0.389 to -0.297; adding cultural distance instead of social connectedness changes the coefficient only to -0.346 (full regressions not reported).

[15] A standard-deviation increase in social connectedness leads to an increase of log loan volumes by 0.245. This increase compensates for an increase in the *logarithm* of physical distance by 0.92. As physical distance enters the regressions in logs, the effect of physical distance is nonlinear. At the median physical distance (413

connectedness in bank lending, which is distinct from physical and cultural distances, and compensates for the lending barriers posed by these distances.[16]

Table 2.4: Social connectedness and the allocation of bank lending

The table provides estimates of how the allocation of cross-county bank lending varies with county pairs' social connectedness. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. *Social connectedness*$_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. *Physical distance*$_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. *Cultural distance*$_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties i and j, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.B.5 reports the coefficients of the control variables. The bottom part of the table informs about the statistical significance of the difference between the coefficients in columns 1 to 3 and those in column 4. The standardized beta coefficients at the end of the table express the effect of a standard-deviation increase in the explanatory variable in standard deviations of the dependent variable. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			
Social connectedness	0.012***			0.007***
	(0.001)			(0.001)
Physical distance		-0.389***		-0.267***
		(0.041)		(0.051)
Cultural distance			-0.034***	-0.016**
			(0.007)	(0.007)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes
No. of obs.	66,684	66,684	66,684	66,684
Adj. R^2	0.519	0.522	0.515	0.525
Adj. R^2 within	0.121	0.126	0.114	0.132
P-value for H0: no difference to coefficient in column (4)				
Social connectedness	0.000			
Physical distance		0.063		
Cultural distance			0.057	
Standardized beta coefficients				
Social connectedness	0.21			0.12
Physical distance		-0.25		-0.17
Cultural distance			-0.13	-0.06

Alternative specifications and the probability of lending As discussed in Section 2.2.1, connectedness and distances are slow-moving or time-invariant, which is why we obtain our baseline estimates based on cross-sectional data. However, the relationship between loan allocations and social connectedness is not limited to this cross section. For the regressions reported in columns 1 and 2 of Table 2.5, we exploit a panel dataset that covers the

miles), the increase in the logarithm of physical distance corresponds to an increase in physical distance of 621 miles.

[16]The results hold within and across states and thus cannot be explained by changes in regulation at state borders (see Table 2.B.6 in the appendix).

years 2004 to 2018. In column 1, we re-estimate our baseline regression (compare Table 2.4, column 4). The results are robust. More importantly, the same applies to the results in column 2, where we include source-county-time and destination-county-time fixed effects. We can thus exclude that our results are driven by county-time-specific credit demand or the economic development in the bank's home county. When estimating time-varying coefficients of social connectedness by interacting the variable with time dummies, loan volumes significantly increase during each of the 15 years and the size of the increase is stable over time (see Figure 2.B.1 in the appendix). The panel estimates thus strongly support that cross-county lending increases with social connectedness.

Table 2.5: Choice of sample, additional fixed effects, and the probability of lending

This table illustrates the robustness of our results with respect to the construction of our sample and additional fixed effects. Furthermore, it explores the relationship between social connectedness and the probability of lending between county pairs. In columns 1 and 2, the dependent variable, $log(volume\ of\ SME\ loans)_{i,j,t}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j in year t (2004 - 2018). Columns 3 and 4 are based on a cross-sectional sample, which also includes the county pairs that do not experience any cross-county lending. The dependent variable in column 3 is $log(volume\ of\ SME\ loans)_{i,j}$. Column 4 analyzes the probability of a lending relationship between county pairs using a $lending\ indicator_{i,j}$ as dependent variable that equals one if there is any lending from banks in county i to SMEs in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables account for the GDP growth and unemployment differentials, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Figure 2.B.1 displays the evolution of the effect of social connectedness over time. Table 2.B.7 reports additional cross-sectional specifications. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			Lending indicator
Social connectedness	0.006***	0.006***	0.003***	0.0002***
	(0.001)	(0.001)	(0.000)	(0.000)
Physical distance	-0.272***	-0.285***	-0.143***	-0.008***
	(0.052)	(0.053)	(0.013)	(0.001)
Cultural distance	-0.017***	-0.017***	-0.004***	-0.0002**
	(0.006)	(0.006)	(0.001)	(0.000)
Source county FE	Yes	No	Yes	Yes
Destination county FE	Yes	No	Yes	Yes
Source-county-time FE	No	Yes	No	No
Destination-county-time FE	No	Yes	No	No
County-pair-level control variables	Yes	Yes	Yes	Yes
No. of obs.	788,817	788,817	9,526,482	9,526,482
Adj. R^2	0.482	0.542	0.337	0.332
Adj. R^2 within	0.142	0.155	0.077	0.068

Next, we move back to cross-sectional data, but include also those county pairs that do not experience any lending (refer to the discussion toward the end of Section 2.3.1). Again our results are maintained (column 5). More interestingly, including all county pairs allows us to analyze the relationship between social connectedness and the probability that any lending takes place at all. Column 6 reports estimates of a linear probability model in which the regression specification deviates from our baseline regression only in that the dependent variable now is a dummy variable that equals 1 if there is at least some lending from source to destination county. The lending probability significantly increases with social connectedness, as the coefficient is positive and statistically significant. Specifically, an increase in social connectedness by one percentage point is associated with a 0.02 percentage point higher lending probability, which corresponds to a 3% increase relative to the average probability of a lending relationship. The results also hold when restricting the sample to counties that are less far apart, such that lending is more likely to take place (see Table 2.B.7 in the appendix). Hence, social connectedness increases cross-county lending both at the intensive and at the extensive margin.

Instrumental variable approaches As illustrated above, bank lending increases with social connectedness across a broad set of specifications, which include a variety of fixed effects. We also control for a large set of variables that may drive bank lending and are related to social connectedness, such as migration, trade, and commuting. Nevertheless, our estimates are not based on a natural experiment. In this section, we propose four instrumental variable approaches to address potentially remaining endogeneity concerns. The first three instruments are based on a historical travel cost argument. These costs do not have a direct effect on bank lending today but may have shaped social ties in the past, some of which may have persisted for generations. Compared to our baseline specification, we additionally control for present-day travel costs, such that our results cannot be explained by a correlation between historical and current travel costs. The fourth instrument exploits the quasi-random staggered introduction of Facebook across the United States, which was again not causally related to bank lending but may have shaped social connectedness, as Facebook offers a way to stay in touch.

For our first instrument, we obtain data on county-to-county highway connections from Baum-Snow (2007), who also provides highway construction dates. U.S. highways were planned during World War II to improve logistics for the war efforts and were built in the aftermath of the war, partly to facilitate a quick relocation of resources during the Cold War.

While the founding fathers of the highway network were thus not motivated by considerations related to bank lending, it is conceivable that social ties have emerged along highways and that these historical social ties are persistent. To exploit this idea, we define an indicator variable that equals 1 whenever two counties are connected by the same highway and use this variable as an instrument for social connectedness. Column 1 of Table 2.6 reports the results. As expected, social connectedness is higher for counties that are connected by the same highway (see coefficient of the first-stage regression at the bottom of the table).[17] A test for the significance of the coefficient returns an F-value of 53, providing no indication of a weak instrument. In the second-stage regression, the coefficient of social connectedness is positive and statistically significant. The coefficients of physical and cultural distance remain negative but culture does not enter the regression significantly anymore. Hence, the results support our findings on social connectedness and emphasize its comparably large effect on bank lending.

While social ties indeed appear to have emerged along highways, they likely did so slowly over time. To incorporate this idea, our next instrument measures the number of years that have passed since the construction of a highway that connects two counties. As can be seen in column 2 of Table 2.6, social connectedness is larger the longer a highway connection existed and the F-test rejects the presence of a weak instrument with an F-value of 48. The second-stage regression estimates indicate that a one-point increase in the social connectedness index leads to a 3.3% increase in the loan volume, which is almost identical to the results from our first instrument. We also assess the robustness of our first two instrumental-variable regressions by excluding those counties that the highways were primarily meant to connect. Specifically, we exclude particularly urban counties (i.e., beyond the 75th percentile of the distribution). The results are robust (see Table 2.B.9, columns 1 and 2).

For our third instrument, we obtain data from Donaldson and Hornbeck (2016), who calculate travel costs for the time after the Westward Expansion, that is, the late 19th and early 20th century. The county-to-county costs are computed as the cheapest combination of traveling by railways, canals, and cattle paths. We use the latest available data (1920), as connectedness patterns were less persistent while the railway network was still under

[17] Table 2.B.8 reports the full first-stage regression results.

construction.[18] Similar to our first two instruments, the historical travel costs significantly correlate with social connectedness in the first stage and we find no indication of a weak instrument (F-value equals 142). In the second-stage regression, the coefficients of physical and cultural distance are again negative but insignificant, whereas social connectedness has a strong positive effect on loan volumes. Overall, all three instruments based on historical travel cost arguments emphasize that social connectedness significantly increases cross-county lending.

As an alternative approach, we exploit the quasi-random staggered introduction of Facebook as an instrument. Created by Mark Zuckerberg and his colleagues in the dorm rooms of Harvard University, Facebook memberships were initially restricted to students from this university.[19] Later on, the online network was gradually opened to other Ivy League colleges and, afterward, in a quasi-random fashion to other universities. Due to the initial pattern, we subsequently exclude counties that host Ivy League colleges. We track how Facebook spread across the United States by manually recovering the order in which the first student of a university created a Facebook account.[20] We combine this hand-collected information with university locations and rank counties by the appearance of Facebook in these counties.[21] The instrument is then defined as follows:

$$Facebook\ rollout = \frac{Rank_i + Rank_j}{Student\ population_i + Student\ population_j}\ . \tag{2.7}$$

$Rank_i$ ($Rank_j$) is the rank number of county i (j). We scale this sum by the student populations at the time of the rollout (i.e., 2005) to account for the possibility that universities with more students joined Facebook earlier simply because of the larger number of students.

[18]The F-value of the test for significance of the instrument in the first-stage regression decreases the further we go back in time. We can go back as far as 1880 before the instrument becomes weak. Until then, the results are independent of the choice of year (regressions not reported).

[19]The restriction was enforced by allowing access only to students with a Harvard University email address.

[20]During the early times of Facebook, members' profile IDs were constructed such that a) students of the same university could be identified based on their user IDs and b) higher user IDs corresponded to universities joining later. Together with publicly available information about which universities early Facebook users studied at, this information enables us to recover the order in which universities gained access to Facebook.

[21]In some regions, Facebook only took off after the construction of user IDs had been randomized. We set the rank of these late joiners to the maximum value of the rank distribution plus one standard deviation.

Table 2.6: Social connectedness and loan allocations: instrumental-variable approaches

The table provides instrumental-variable estimates for our baseline regression (see Equation 2.1 and Table 2.4, column 4), exploiting historical travel costs and the rollout of Facebook as instruments for social connectedness. The bottom part of the table reports first-stage coefficients, p-values, and F-statistics of the instruments. Table 2.B.8 reports full first-stage regressions. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county *i* to small and medium-sized enterprises in county *j*. The instrument in column 1, $same\ highway_{i,j}$, is an indicator variable that equals one if counties *i* and *j* are connected by the same highway. $Years\ since\ construction_{i,j}$, the instrument in column 2, equals the number of years for which counties *i* and *j* have been connected by the same highway. $Historical\ travel\ costs_{i,j}$ (column 3) corresponds to the costs of traveling from county *i* to county *j* in 1920. $Facebook\ rollout_{i,j}$ (column 4) is an index that relies on the order in which Facebook became available in counties *i* and *j*. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county *i* and a person in county *j* are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties *i* and *j* in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties *i* and *j* in percent of the maximum cultural distance between any two U.S. counties. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties *i* and *j*, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. In columns 1 to 3, we additionally control for present-day highway-travel costs between counties *i* and *j*. In column 4, we use an *absolute* measure of social connectedness while additionally controlling for the inverse population product of the county pair to exclude a mechanical correlation between the *relative* county rank used to construct the Facebook-rollout instrument and the *relative* social connectedness. The results are robust to using relative social connectedness (see Table 2.B.9, column 3). Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			
Instrument:	Same highway	Years since construction	Historical travel costs	Facebook rollout
Social connectedness	0.032***	0.033***	0.024***	0.012**
	(0.011)	(0.011)	(0.005)	(0.006)
Physical distance	-0.342**	-0.333*	-0.509***	-0.187
	(0.165)	(0.172)	(0.108)	(0.118)
Cultural distance	-0.005	-0.004	-0.008	0.007
	(0.009)	(0.009)	(0.007)	(0.008)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes
Present-day travel costs	Yes	Yes	Yes	No
No. of obs.	66,647	66,647	56,223	56,852
Adj. R^2	0.496	0.494	0.520	0.539
Adj. R^2 within	0.078	0.075	0.113	0.114
Instrument (1st stage)	3.783***	0.071***	4.105***	163.1***
	(0.000)	(0.000)	(0.000)	(0.000)
F-value (1st stage)	53.3	48.1	142.1	151.2

Column 4 of Table 2.6 displays the results based on the Facebook rollout as an instrument.[22] The instrument significantly correlates with social connectedness (the F-value equals

[22] In this regression, we use an absolute measure of social connectedness to avoid a mechanical correlation between the denominator of the instrument (student populations) and the denominator of the social connectedness index (total populations) and, instead, add the population product as an additional control variable. The results are qualitatively robust when we follow our usual specification (see Table 2.B.9, column 4). However, in that case, the second-stage coefficient of social connectedness appears inflated, such that we believe it to be prudent to emphasize our main instrumental-variable results in Table 2.6.

163). According to the second-stage estimates and in line with our other instrumental variable approaches, social connectedness significantly increases loan volumes. Overall, the results thus strongly emphasize social connectedness as a key driver of loan allocations.

2.4.1.2 Information sensitivity of lending

The previous findings are consistent with social ties facilitating banks' access to soft information. Subsequently, we explore the information channel more closely by analyzing how the effect of social connectedness depends on the information sensitivity of loans.

Banks, borrowers, and the economic environment Lending processes tend to be less standardized in small banks, which leaves more room for soft information to feed into lending decisions. Based on this idea, we begin our analysis of the information channel by adding an interaction term between social connectedness and bank size to our baseline regression (compare Equation 2.1). Bank size is defined as the logarithm of the loan-volume-weighted average total assets of all banks that lend from source to destination county. Table 2.7, column 1, reports the results. Social connectedness indeed increases loan volumes more strongly for smaller banks. Based on this regression, a plot of the effect of social connectedness at different levels of bank size shows that the effect of social connectedness is three times as large as our baseline estimate for county pairs that predominantly experience lending from small banks, whereas the effect becomes just insignificant for the very largest banks (Figure 2.B.2, panel (a)). In column 2, we interact social connectedness with the borrower county's exposure to industry volatility. To calculate this variable, we weight the U.S.-wide output volatility of industries with a county's industry shares. Banks are likely to find it more difficult to judge a small or medium-sized enterprise's ability to repay if they expect this firm to operate in a more unpredictable economic environment. Our results indicate that the effect of social connectedness is larger for those more opaque borrowers, as the coefficient of the interaction term is positive and statistically significant while the coefficient of social connectedness remains positive and significant. The coefficients imply that loan volumes to counties that are exposed to volatile industries (e.g., agriculture, forestry, fishing, and hunting) increase 50% more than loan volumes to counties that are exposed to more stable industries (e.g., educational services).[23] We thus find preliminary evidence that social connectedness affects lending decisions more strongly if banks are more in need of information.

Next, we interact social connectedness with deciles of GDP growth in the borrower's county. If the effect of social connectedness is related to loan officers lending to peers who struggle to obtain funding, we would expect social connectedness to increase loan volumes especially in counties where economic conditions are weak. Our estimates, however, show that the effect of social connectedness is stronger both in borrower counties that experience particularly low and those that experience particularly high GDP growth. The coefficient of social connectedness, which represents the effect of social connectedness at the 5th decile of borrower-county GDP growth, is positive and statistically significant, as are the interactions between social connectedness and the first two and the last decile (column 3). Providing further evidence of the information channel, we thus find evidence that social connectedness increases lending most strongly when banks are confronted with an unusual local economic development such as a strong boom that might signal unsustainable growth or a strong bust, e.g. related to a larger firm that moves its production away from the borrower county.

Lastly, banks may have a higher need for information when lending to an economic environment that develops differently from their home market. To exploit this idea, we interact social connectedness with deciles of the GDP growth differential between source and destination county. The coefficient of social connectedness and its interaction with the four highest deciles of the GDP growth differential are positive and significant, whereas all other interactions do not enter the regression significantly (column 4). Hence, bank lending increases more strongly in social connectedness when the local economic environment of the borrower and the lender are particularly different, which again illustrates that social connectedness has stronger effects if the banks' need for information is high.

Loan types To further explore the role of information, we subsequently distinguish between types of loans that differ in their screening incentives. The analysis is based on the mortgage-lending data, which allow the identification of different loan types. In our baseline specification, the effect of social connectedness is smaller in the mortgage loan sample

[23]To be precise, this number applies for a county that is exposed only to agriculture, forestry, fishing, and hunting (volatility exposure = 6.57) compared to a county that is only exposed to educational services (2.96) or any convex combinations of industries with the same volatility exposures.

Table 2.7: Information sensitivity: bank types and borrowers' economic environments

This table reports regressions used to analyze how the relationship between bank lending and social connectedness depends on banks' need for information. Column 1 adds an interaction between social connectedness and $bank\ size_{i,j}$, the logarithm of the loan-volume-weighted average balance sheet size of all banks that lend from county i to county j, to our baseline regression. Column 2 interacts social connectedness with $borrower's\ volatility\ exposure_j$, a measure of borrower opacity calculated using county j's industry shares to weight the U.S.-wide output volatility of industries. Column 3 and 4 interact social connectedness with dummy variables that indicate deciles of the destination-county (j) GDP growth or the source (i) and destination (j) counties' GDP growth differential instead. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two U.S. counties. Control variables vary at the county-pair level and consist of the physical and cultural distances, the GDP growth and unemployment differentials, gross migration and trade, the share of the commuting population, same state and common border indicator variables, and the single terms of interactions. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			
Social connectedness	0.037***	0.007***	0.006***	0.006***
	(0.006)	(0.001)	(0.001)	(0.001)
Social connectedness · Bank size	-0.002***			
	(0.000)			
Social connectedness · Borrower's volatility exposure		0.001***		
		(0.000)		
Social connectedness · GDP growth decile 1			0.002**	
			(0.001)	
Social connectedness · GDP growth decile 2			0.003***	
			(0.001)	
Social connectedness · GDP growth decile 3			0.001	
			(0.001)	
Social connectedness · GDP growth decile 4			0.001	
			(0.001)	
Social connectedness · GDP growth decile 6			0.000	
			(0.001)	
Social connectedness · GDP growth decile 7			0.000	
			(0.001)	
Social connectedness · GDP growth decile 8			0.001	
			(0.001)	
Social connectedness · GDP growth decile 9			0.001	
			(0.001)	
Social connectedness · GDP growth decile 10			0.003***	
			(0.001)	
Social connectedness · GDP growth differential decile 2				-0.000
				(0.001)
Social connectedness · GDP growth differential decile 3				-0.000
				(0.001)
Social connectedness · GDP growth differential decile 4				-0.000
				(0.001)
Social connectedness · GDP growth differential decile 5				0.000
				(0.001)
Social connectedness · GDP growth differential decile 6				0.001
				(0.001)
Social connectedness · GDP growth differential decile 7				0.003***
				(0.001)
Social connectedness · GDP growth differential decile 8				0.003***
				(0.001)
Social connectedness · GDP growth differential decile 9				0.002*
				(0.001)
Social connectedness · GDP growth differential decile 10				0.002**
				(0.001)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
Physical and cultural distances	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes
No. of obs.	66,684	66,684	66,684	66,684
Adj. R^2	0.551	0.525	0.525	0.525
Adj. R^2 within	0.181	0.132	0.132	0.132

than in the SME sample (see Table 2.B.10 and the standardized beta coefficients therein). This also points to an information channel, as the credit intermediation process tends to be less standardized for SME loans and small and medium-sized enterprises are more opaque borrowers, such that soft information is more important for SME lending than for mortgage lending.

Our first distinction between mortgage loan types is based on government guarantees. These guarantees protect banks from default risk, which reduces screening incentives and, hence, makes information less valuable. We aggregate cross-county mortgage loans with and without guarantees separately and run our baseline regression on these two different subsets. Table 2.8, column 1, displays the results for loans which are *not* backed by government guarantees. For these loans, the coefficient of social connectedness is highly significant and equals 0.016, which is almost twice as large as in the overall sample (0.009, compare Table 2.B.10, column 2). Conversely, social connectedness is not significantly related to lending for loans that are backed by government guarantees (column 2 of Table 2.8). We formally test if the effect of social connectedness significantly differs across the two loan types by adding an interaction term between social connectedness and the share of the volume of guaranteed loans to our baseline regression (column 3). In line with our previous findings, loan volumes significantly increase with social connectedness, but the effect becomes significantly smaller the higher the guaranteed share. Supporting our earlier reasoning, social networks thus play an important role in bank lending if banks bear the risk of a loan, thus having an incentive to screen and to make use of the information flowing through these networks.

As an additional source of variation in the information sensitivity of lending, we next distinguish between loans that are kept on the originating bank's balance sheet and loans that are securitized. Banks reduce screening activities for securitized loans but the incentives to screen are not entirely eliminated because of reputation concerns (Keys et al., 2010; Purnanandam, 2011; Keys, Seru, and Vig, 2012; Wang and Xia, 2014).[24] Hence, access to information through social networks should be less relevant for these loans. While the coefficient of social connectedness is positive and statistically significant in both samples, loan volumes increase twice as much in social connectedness for loans that are kept on the books

[24] For a discussion of agency conflicts in securitization see, for instance, Fenner, Klein, and Mössinger (2019).

compared to loans that are securitized (Table 2.8, columns 4 and 5). Again, we test whether the difference in the effect of social connectedness across loan types is statistically significant based on an interaction between social connectedness and the share of the volume of securitized loans (column 6). The estimates support the existence of the differential effect.

Table 2.8: Information sensitivity: loan types

The regressions in this table estimate how the relationship between bank lending and social connectedness depends on banks' screening incentives. Columns 1, 2, 4, and 5 use sample splits based on government guarantees and securitization. The number of observations is identical to the full sample as we perform the sample splits at the loan level, meaning before aggregating the loan volumes at the county-pair level. Columns 3 and 6 use interaction terms with continuous variables instead of sample splits. The dependent variable, $log(volume\ of\ mortgage\ loans)_{i,j}$, is the logarithm of the total volume of all mortgage loans of the loan type indicated in the table's second row, provided from banks in county *i* to borrowers in county *j*. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county *i* and a person in county *j* are acquainted with each other, measured in percent of the maximum social connectedness between any two U.S. counties. $Guaranteed\ share_{i,j}$ refers to the share of the loan volume subject to government guarantees. $Sold\ share_{i,j}$ refers to the share of the loan volume sold off book. These two shares are additionally included as single terms in columns 3 and 6, respectively. Control variables also vary at the county-pair level and consist of the physical and cultural distances, the GDP growth and unemployment differentials, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

Dep. var.: log(Volume of mortgage loans ...)	(1) without guarantees	(2) with guarantees	(3) of both types	(4) kept on book	(5) sold off book	(6) of both types
Social connectedness	0.016***	0.004	0.012***	0.016***	0.008**	0.022***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Social connectedness · Guaranteed share			-0.032***			
			(0.004)			
Social connectedness · Sold share						-0.038***
						(0.003)
Source county FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes	Yes	Yes
Physical and cultural distances	Yes	Yes	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	34,483	34,483	34,483	34,483	34,483	34,483
Adj. R^2	0.262	0.295	0.337	0.363	0.317	0.583
Adj. R^2 within	0.065	0.041	0.255	0.102	0.044	0.530

Overall, the results in this section demonstrate that social connectedness increases cross-county lending, especially if banks have a high need for information and strong screening incentives. The findings thus strongly support that social connectedness plays an important role in bank lending *because* banks can leverage their social network as a source of information.

2.4.2 Lending risk and loan performance

Above, we have analyzed how social connectedness affects which counties banks lend to. Subsequently, we explore whether the type of borrowers that receive loans (risky vs. less risky), the loan conditions (interest rate), and the performance of loans also differs across social connectedness. This allows us to further investigate the information channel and to assess consequences of social connectedness altering banks' lending decisions. The analysis exploits our loan-level sample of mortgage loans (see Section 2.3.2). Table 2.9 reports the results.

In column 1, we regress the borrower's FICO score at the time of origination of the loan on social connectedness, while controlling for physical and cultural distance, and bank and origination-year fixed effects (see Equation 2.2 in Section 2.2.2). The coefficient of social connectedness is insignificant. Borrowers' creditworthiness thus is not heterogeneous across social connectedness. In column 2, we estimate the same model to explain loan-to-value (LTV) ratios. The coefficient of social connectedness is again not statistically significant. From an ex-ante perspective, the riskiness of a loan is thus independent of the social ties between a borrower's and a bank's regions.

In column 3, we use the interest rate (in basis points) as the dependent variable while additionally controlling for the FICO score and the LTV ratio, the loan volume (in logs), the debt-to-income ratio, and a binary variable that indicates first-time home buyers. In line with expectations, the estimates indicate that the interest rate decreases with a borrower's creditworthiness but increases with their LTV ratio. More importantly, the coefficient of social connectedness is negative and statistically significant. According to our estimates, borrowers with a standard deviation higher social connectedness pay a 2.7 basis points lower interest rate (=40*(-0.068)), which equals 3% of a standard deviation of the interest rate (83). Hence, borrowers from well-connected counties not only receive more lending, but they also have access to cheaper financing.

To analyze how social connectedness relates to the ex-post loan performance, our next dependent variable indicates delinquent loans. The variable equals 1 if a loan has been at least 90 days past due at least once. The estimates reveal no statistically significant relationship between the probability of delinquency and social connectedness (column 4). In column 5, we focus on more extreme cases, namely loans that actually default. Specifically, we regress the unpaid balance on social connectedness and an interaction of social connectedness and a dummy variable that equals 1 if a loan is *not* in default. The coefficient of social connectedness is negative and statistically significant. Its sum with the interaction term is insignificant. Hence, controlling for the original loan amount, the origination year, the ex-ante riskiness, and further loan characteristics, the remaining loan amount significantly decreases with social connectedness *for those loans that are in default*. Specifically, the estimates imply that borrowers who default owe the bank 80% less if they are from a region with one standard deviation higher social connectedness. Banks thus profit from superior performance of loans to well-connected regions.

Table 2.9: Ex-ante lending risk and ex-post loan performance

This table reports loan-level regressions that explain borrower characteristics, loan characteristics, and loan performance by social connectedness to explore how social connectedness relates to the ex-ante and ex-post riskiness of loans. The sample comprises mortgage loans originated between 2000 and 2008, observed until 2018. $FICO\ score_l$ is an index that measures the borrower's credit worthiness at the time of the origination of loan l. $Combined\ LTV_l$ is the combined loan-to-value ratio of all mortgages on the borrower's property at the time of origination. The *interest rate*$_l$ of loan l, also as of origination, is measured in basis points. $Delinquent_l$ is a dummy variable which indicates mortgages that have been at least 90 days past due at least once. For readability of the coefficients, the delinquent dummy enters regressions as a share of its standard deviation. $Unpaid\ balance_l$ equals the amount of loan l still owed by a borrower and enters the regression in logs. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two U.S. counties. All columns control for the physical and cultural distances between borrower and lender. The additional loan characteristics in columns 3 to 5 are the natural logarithm of the initial loan volume, the initial debt-to-income ratio, and a binary variable indicating first-time home buyers. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)
Timing relative to lending decision:	Ex ante		During	Ex post	
Dependent variable:	FICO score	Combined LTV	Interest rate	Delinquent	log(Unpaid balance)
Social connectedness	0.004	-0.017	-0.068**	0.001	-0.020*
	(0.036)	(0.012)	(0.031)	(0.001)	(0.011)
Social connectedness · Not in default					0.017
					(0.011)
FICO score			-0.092***	-0.004***	0.004***
			(0.008)	(0.000)	(0.001)
Combined LTV			0.454***	0.003***	-0.005*
			(0.024)	(0.001)	(0.003)
Interest rate				0.001***	0.002
				(0.000)	(0.002)
Delinquent					0.134***
					(0.041)
Bank FE	Yes	Yes	Yes	Yes	Yes
Origination year FE	Yes	Yes	Yes	Yes	Yes
Physical and cultural distances	Yes	Yes	Yes	Yes	Yes
Additional loan characteristics	No	No	Yes	Yes	Yes
No. of obs.	20,760	20,760	20,760	20,760	20,760
Adj. R^2	0.024	0.039	0.770	0.092	0.083
Adj. R^2 within	0.000	0.000	0.085	0.073	0.005

Overall, the loan-level analysis shows that social connectedness is not associated with lending to riskier borrowers. However, borrowers from well-connected counties pay lower interest rates. This result is in line with both a lower cost of information acquisition for banks and their expectation of improved loan performance due to access to superior information.

We indeed find evidence of improved performance of loans. While delinquency rates do not differ across social connectedness, defaulting loans cause much smaller losses if social connectedness is high. Since social connectedness is not associated with an increased ex-ante riskiness of lending, the results are in stark contrast to the effects of a preferential treatment of peers that results in the financing of negative NPV projects. Instead, the results are in line with social ties facilitating banks' access to information, which can benefit both borrowers and banks.

2.4.3 Real effects

To further explore the consequences of the role of social connectedness in bank lending, we subsequently analyze the real effects of borrower counties' social proximity to bank capital. The analysis is based on our county-level dataset, for which we aggregate the county-pair-level social connectedness at the county level by calculating a borrower county's social proximity as its average social connectedness to all counties weighted by total bank assets in these counties (see Section 2.3.3). Table 2.10 reports the results of our analysis.

In column 1, we regress the volume of SME loans to the borrower county (in logs) on social proximity, while controlling for physical and cultural proximity, county- and state-time fixed effects, industry shares, commuting, and migration (see Equation 2.3 in Section 2.2.3). The coefficient of social proximity is positive and statistically significant. It indicates that a standard-deviation increase in a county's social proximity to bank capital increases the total volume of SME lending to that county by 4.7%. In line with our earlier findings, borrowers from regions with closer social ties to banks' regions receive more lending.

In column 2, we re-estimate our model with real GDP growth as the dependent variable. The coefficient of social proximity is positive and highly significant. According to our estimates, counties with one standard deviation higher social proximity to bank capital experience 0.85 percentage points higher GDP growth. Note that *county*-level GDP growth generally fluctuates more than *country*-level growth. The 0.85 percentage points increase equals an increase of 11% (=0.85/7.6) of a standard deviation of GDP growth, which is sizable and well in line with a long list of studies of the real effects of access to bank funding.[25]

[25] Starting from Jayaratne and Strahan (1996) and Levine and Zervos (1998) to recent studies such as Huber (2018).

In column 3, we additionally interact social proximity with the percentage of small firms in the borrower county. Small firms tend to rely more on bank lending for financing. The coefficient of social connectedness and the coefficient of its interaction with the small-firm percentage are positive and statistically significant. Hence, GDP growth increases more strongly with social proximity in counties with many small firms.

Table 2.10: Real effects of social proximity to bank capital

This table reports county-year-level analyses of the real effects of social proximity to bank capital (see Equation 2.5). The sample covers the years 2009 to 2017. $Loan\ volume_{i,t}$ is the volume of loans to small and medium-sized enterprises in county i in year t. $Real\ GDP\ growth_{i,t}$ and $log(employment)_{i,t}$ refer to county i's GDP growth and log employment in year t. County i's $social\ proximity_{i,t}$ in year t is defined as $\sum_j social\ connectedness_{i,j} \cdot total\ assets_{j,t}$, where $social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other and $total\ assets_{j,t}$ is the sum of total assets of all banks with headquarters in county j in year t (see Section 2.3.3 for a detailed discussion). For ease of interpretation, $social\ proximity_{i,t}$ is scaled to a standard deviation of 1. Control variables account for the physical and cultural proximity to bank capital, industry shares, and, in columns 4 and 5, commuting and migration. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the county level. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	log(Loan volume)	Real GDP growth		log(Employment)	
Social proximity	0.047**	0.850***	0.638**	0.004**	0.003
	(0.021)	(0.274)	(0.263)	(0.002)	(0.002)
Social proximity · Small-firm percentage			0.0373**		0.0003**
			(0.0159)		(0.0001)
Small-firm percentage			0.919***		0.000
			(0.302)		(0.001)
County FE	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes
Physical and cultural proximity	Yes	Yes	Yes	Yes	Yes
Additional control variables	Yes	Yes	Yes	Yes	Yes
No. of obs.	24,152	24,161	24,161	24,161	24,161
Adj. R^2	0.968	0.240	0.241	0.999	0.999
Adj. R^2 within	0.004	0.131	0.132	0.136	0.137

Similar findings hold for employment. In columns 4 and 5 we use the number of employed people (in logs) as dependent variable. Employment significantly increases with social connectedness (column 4). A standard-deviation increase in a county's social proximity is associated with a 0.4% increase in employment. This increase is again larger for counties with a higher percentage of small firms, as indicated by the positive and significant interaction term in column 5. The size of the increase is again in line with the literature.[26]

[26] For instance, Huber (2018) estimates that a standard-deviation increase in a county's dependence on a weakly capitalized major bank reduces county-level employment by 0.83% in Germany.

Overall, counties with higher social proximity to bank capital receive more lending and have higher GDP growth and more employment. We thus find strong additional evidence that borrowers profit from strong social ties between their own region and a bank's region.

2.5 Additional analyses and robustness checks

This section provides two types of additional analyses that complement our findings on cross-county lending. First, it analyzes how the effects of connectedness and distances depend on each other. Second, it assesses the robustness of our baseline results with respect to alternative measures of physical and cultural distance. Thereby, this section reaffirms that our results are independent of the chosen measurement approaches and that the effects of social connectedness are distinct from physical and cultural distances.

2.5.1 Heterogeneities across distances

The findings in Section 2.4.1.1 clearly illustrate the potential of social ties to compensate for the lending barriers posed by physical and cultural distance. This section explores nonlinear effects of social connectedness. In so doing, it also takes the analysis one step further and discusses whether the lending barriers associated with distances disappear in the case of sufficiently close social ties.

Table 2.11 displays the results. For ease of comparability, column 1 restates our baseline regression from Table 2.4, column 4. We begin the discussion of nonlinear effects by analyzing whether the effect of social connectedness depends on its level. To this end, we add a squared term of this variable to our baseline regression. Our baseline estimates remain unchanged and the coefficient of the squared term is not statistically significant (column 2). Hence, loan volumes increase linearly in social connectedness.

More interestingly, we explore whether social ties become more or less important for lending decisions as the physical distance between borrower and lender increases. The results suggest the latter. Whereas the coefficient of social connectedness remains significantly positive, the coefficient of its interaction with physical distance is negative and statistically significant (column 3). As distance increases, the positive effect of social connectedness on loan volumes decreases. We conjecture that this decreasing effect is associated with a decreasing *intensity* of social ties (as opposed to their number) at larger distances, where opportunities for face-to-face contact are more rare. As a result, distant contacts exchange less information, making them less valuable for bank-lending decisions.

Table 2.11: Heterogeneities across distances

The regressions reported in this table estimate the dependence of the relationship between bank lending and social connectedness on distances and connectedness. Column 1 restates the baseline regression from Table 2.4, column 4. Columns 2 to 4 add a squared term of social connectedness or interactions between social connectedness and the two distance measures to our baseline regression. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			
Social connectedness	0.007***	0.007**	0.022***	0.002*
	(0.001)	(0.003)	(0.004)	(0.001)
Social connectedness^2		-0.000		
		(0.000)		
Social connectedness · Physical distance			-0.004***	
			(0.001)	
Social connectedness · Cultural distance				0.0004***
				(0.0001)
Physical distance	-0.267***	-0.264***	-0.251***	-0.247***
	(0.051)	(0.055)	(0.051)	(0.053)
Cultural distance	-0.016**	-0.015**	-0.017**	-0.021***
	(0.007)	(0.007)	(0.007)	(0.008)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
County-pair level control variables	Yes	Yes	Yes	Yes
No. of obs.	66,684	66,684	66,684	66,684
Adj. R^2	0.525	0.525	0.526	0.526
Adj. R^2 within	0.132	0.132	0.133	0.134

Whereas the effect of social connectedness decreases with physical distance, it increases with cultural distance. When extending our baseline specification by an interaction term between social connectedness and cultural distance, its coefficient is positive and significant (column 4). The coefficient of social connectedness remains significantly positive. Hence, loan volumes increase with social connectedness, but this relationship is particularly pronounced at large cultural distances. In fact, the negative effect of cultural distance disappears entirely in the case of sufficiently close social ties in our sample. Social connections thus bridge a cultural divide between borrower and lender. The channel for this effect can be twofold. First, the information flowing through social networks may reduce statistical discrimination that emerges if loan officers with one cultural background lack the information to fully assess loan applicants from a differing cultural background. Second, strong social ties may overcome discrimination due to (subconscious) prejudices against people of unfamiliar cultural backgrounds. In both ways, social connectedness may reduce the lending barrier posed by cultural differences.

2.5.2 Alternative measures of physical distance

In our baseline regressions, physical distance is measured as the great-circle distance (i.e., "as the crow flies") between two counties, where county locations are based on the geographical center of a county. If two neighboring counties each host a city close to their common border, social connectedness and cross-county lending may both be increased due to the lower physical distance. This, however, would not be reflected by our measure. While we control for counties that share a common border in all our regressions, we subsequently assess this alternative explanation for our results more closely. Specifically, we define physical distance as the great-circle distance between *population-weighted* county centroids. Column 1 of Table 2.12 restates our baseline results from Table 2.4, column 4. When employing the alternative definition of physical distance, the coefficients of social connectedness and cultural distance remain identical, while the coefficient of physical distance decreases slightly but remains statistically highly significant (column 2). Our results thus cannot be explained by an imprecise identification of cities that are located close to county borders.

A similar argument applies to the infrastructure between borrower and lender. For example, a more convenient road connection between borrower and lender may simultaneously increase social connectedness and lending, which our measure of physical distance cannot fully account for. To assess this hypothetical explanation for our findings, we use the data on county-to-county road travel costs from the Oak Ridge National Laboratory's National Transportation Center as an alternative measure of physical distance. Once again, the results are unchanged as the coefficients of social connectedness, physical distance, and cultural distance are almost identical to our baseline estimates (column 3). The same applies when accounting for the cheapest combination of road, railway, and waterway travel (column 4). Consequently, our results are robust across measures of physical distance, which supports that the effect of social connectedness is distinct from physical distance.

Table 2.12: Alternative measures of physical distance

This table illustrates the robustness of our results with respect to alternative measures of physical distance. Column 1 restates the baseline regression from Table 2.4, column 4. Columns 2 to 4 re-estimate the baseline regressions with alternative measures of physical distance. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. In column 2, physical distance is calculated based on population-weighted county centroids. $Highway\ travel\ costs_{i,j}$ is an index that quantifies the costs of driving from county i to county j. $All\ modes\ travel\ costs_{i,j}$ calculates the travel costs between counties i and j as the cheapest combination of highways, railroads, and waterways. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Control variables also vary at county-pair level and consist of the GDP growth and unemployment differentials, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			
Social connectedness	0.007***	0.007***	0.007***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Physical distance	-0.267***			
	(0.051)			
Physical distance (population-weighted centroids)		-0.253***		
		(0.051)		
Highway travel costs			-0.260***	
			(0.057)	
All modes travel costs				-0.263***
				(0.057)
Cultural distance	-0.016**	-0.016**	-0.017**	-0.018**
	(0.007)	(0.007)	(0.007)	(0.007)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes
No. of obs.	66,647	66,647	66,647	66,647
Adj. R^2	0.525	0.525	0.524	0.524
Adj. R^2 within	0.132	0.131	0.130	0.130

2.5.3 Alternative measures of cultural differences

To construct our measure of cultural distance, we combine information on ethnic ancestries, racial origins, religious beliefs, and the structure of people's social environment into a single variable. This variable has the advantage of being interpretable as the cultural distance between two counties. However, the aggregation requires us to weight the underlying information (see Section 2.3.1). Subsequently, we explore the robustness of our results with respect to the method of aggregation and the overall measurement approach.

Table 2.13 reports the results. Column 1 restates our baseline regression from Table 2.4, column 4. In column 2, we include the four dimensions of cultural identity separately. The effect of social connectedness remains unchanged and loan volumes decrease only slightly more in physical distance compared to our baseline estimates. The sign of the coefficients of all four cultural variables is negative, indicating that all aspects of cultural differences hamper bank lending. However, only the coefficient of the social environment is statistically significant. When we exclude this variable in column 3, the coefficients of the three remaining culture variables are negative, but racial origin now enters the regression significantly. All other results remain unchanged. We can thus exclude that our findings on culture or any other findings are driven by the social-environment dimension in our culture data. In column 4, we include all 39 culture variables separately, without any change to our findings. Consequently, our results are unaffected by how we use the information on cultural backgrounds to account for the cultural distance.

Next, we measure cultural differences based on a different approach. More precisely, we proxy cultural differences with the county-pair-specific vote-share differential for the Republican candidate during the 2016 presidential election, as voting patterns are partially an outcome of cultural patterns (see, for example, Lieske (1993)). Column 5 reports the results for our baseline regression when applying this alternative measure of cultural distance. An increase in the difference of the share of Republican votes by 1 percentage point is associated with a decrease in county-to-county loan volumes by 0.6%. This is in line with our baseline results that cultural differences are – in addition to social connectedness – relevant for lending outcomes even in a within-country setting. Importantly, when using this alternative approach to the measurement of cultural distance, the coefficients of social connectedness and physical distance remain largely unchanged.

Table 2.13: Alternative specifications of cultural distance

This table illustrates the robustness of our results with respect to measures of cultural distance. Column 1 restates the baseline regression from Table 2.4, column 4. Columns 2 and 3 re-estimate the baseline regression while simultaneously including several measures of cultural distance that correspond to different categories of a person's cultural identity (compare the discussion in Section 2.3.1). In column 4, we control for cultural differences by including all 39 absolute differences at county-pair level used to construct our measure of cultural distance (see Table 2.A.2). Column 5 uses the absolute difference of the vote share for the Republican candidate in the 2016 presidential election to proxy for culture. Column 6 adds a measure of the average cultural heterogeneity within the source and destination counties and its interaction with social connectedness to our baseline specification. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties i and j, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	log(Volume of SME loans)					
Social connectedness	0.007***	0.007***	0.007***	0.007***	0.007***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Social connectedness · Cultural het.						-0.009
						(0.007)
Physical distance	-0.267***	-0.285***	-0.277***	-0.314***	-0.295***	-0.273***
	(0.051)	(0.052)	(0.053)	(0.040)	(0.047)	(0.048)
Cultural distance	-0.016**					-0.015**
	(0.007)					(0.007)
Cultural distance: ethnic ancestry		-0.008	-0.027			
		(0.043)	(0.042)			
Cultural distance: racial origin		-0.014	-0.087*			
		(0.054)	(0.045)			
Cultural distance: religious beliefs		-0.003	-0.003			
		(0.059)	(0.060)			
Cultural distance: social environment		-0.125***				
		(0.048)				
Vote-share differential					-0.697**	
					(0.305)	
Source county FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual culture controls	No	No	No	Yes	No	No
No. of obs.	66,684	66,684	66,684	66,684	66,377	66,684
Adj. R^2	0.525	0.525	0.525	0.531	0.525	0.525
Adj. R^2 within	0.132	0.133	0.131	0.144	0.133	0.132

Lastly, we explore whether the relationship between bank lending and social connectedness depends on the cultural heterogeneity in the destination county. To this end, we collect our culture data on the census tract level and calculate the cultural distance between census tracts within a county in the same way in which we calculated the cultural distance between counties.[27] We then calculate the average cultural distance between census tracts per county

[27] We have to leave out the data on religious backgrounds, because it is unavailable at this granular level.

and sum these averages for each county pair. While the coefficient of social connectedness remains positive and significant, the interaction term between cultural heterogeneity and social connectedness is insignificant. Therefore, our findings cannot be explained by social connectedness serving as a proxy for within-county cultural heterogeneity. The results thus provide additional evidence that the relationship between social connectedness and bank lending is distinct from cultural distance.

2.6 Conclusion

This paper analyzes how the geographic structure of social ties affects bank lending. While the previous literature directs its attention toward the lending between peers in exclusive networks or the physical and cultural distance between borrower and lender, we focus on the ubiquitous social network that spans a society. This network can help to overcome asymmetric information by facilitating banks' access to information about borrowers or their local economic environments without requiring a direct link between loan officers and borrowers.

We find that banks from one region lend more to another region if the people who live in these two regions are more connected. This effect of social connectedness is large and compensates for the lending barriers posed by physical and cultural distances. Social connectedness increases bank lending particularly strongly if banks have a high need for information and screening incentives are intact. At the same time, social connectedness does not result in lending to riskier borrowers but is associated with lower borrowing costs and improved loan performance. In addition to higher lending, counties with higher social proximity to bank capital exhibit higher GDP growth and more employment. Consequently, banks and especially borrowers profit from social connectedness, which affects loan allocations because of the information that moves along social ties.

While our results primarily reveal the important role of social connectedness as an information channel in bank lending, they have several potential implications that may also be of interest for future research. Antitrust policies may benefit from taking the structure of social networks into account. Social connectedness increases lending and partly explains the effect of physical distance, meaning that a high concentration of lenders in an area is less concerning if banks outside of this area are well connected to it. Second, social connectedness may help to explain the trend toward geographically more dispersed banking, as banks obtain information through social networks which themselves have become increasingly widespread. Lastly, banks may reduce information asymmetries by employing well-connected agents to obtain information, especially when attempting to expand business in culturally different regions, as the lending barriers posed by different cultural backgrounds disappear when social ties are sufficiently close.

2.A Appendix: lists of variables

Table 2.A.1: Variable definitions and data sources

This table provides variable definitions and data sources. For descriptive statistics on the main sample of cross-county loans to small and medium-sized enterprises see Table 2.1. Tables 2.2, 2.3, and 2.B.4 report descriptive statistics of the additional data used to analyze heterogeneities across the information sensitivity of loans in Section 2.4.1.2, the riskiness of loans in Section 2.4.2, and real effects in Section 2.4.3.

Variable name	Description
Connectedness and distance measures	
Social connectedness	Relative probability of friendship links between source and destination county; scaled to [0;100]; source: Bailey et al. (2018a).
Physical distance	Great-circle distance in miles based on county centroids; source: NBER's county distance database.
Cultural distance	Index quantifying the cultural distance between two counties; scaled to [0,100]; source: own calculation as described in Section 2.3.1.
Bank-lending data at county-pair level	
Volume of SME loans	Volume of newly originated loans to small and medium-sized enterprises from source to destination county; enters regressions in logs; source: CRA.
Volume of mortgage loans	Volume of newly originated mortgage loans from source to destination county; enters regressions in logs; source: HMDA.
Loans without guarantees	Volume of newly originated mortgage loans that are not subject to government guarantees; enters regressions in logs; source: HMDA.
Loans with guarantees	Volume of newly originated mortgage loans that are subject to government guarantees; enters regressions in logs; source: HMDA.
Guaranteed share	Share of the mortgage loan volume subject to government guarantees; source: HMDA.
Loans kept on book	Volume of newly originated mortgage loans that are kept on the originating bank's balance sheet; enters regressions in logs; source: HMDA.
Loans sold (off book)	Volume of newly originated mortgage loans that are sold and thus not kept on the bank's balance sheet; enters regressions in logs; source: HMDA.
Sold share	Share of the mortgage loan volume sold off the books; source: HMDA.
Main control variables at county-pair level	
Common border	Indicator variable equal to 1 if source and destination county are direct neighbors; source: U.S. Census Bureau.
GDP growth differential	Absolute value of the county-pair difference in the average real GDP growth during the last three years; in percentage points; source: U.S. Bureau of Economic Analysis.
Gross commuting	Share of the county-pair population commuting from source to destination county or vice versa; in %; source: U.S. Census Bureau.
Gross migration	Share of the county-pair population which migrated from source to destination county or vice versa; in %; U.S. Census Bureau.
Gross trade	Gross value of trade between source and destination county; in million USD; source: U.S. Census Bureau.
Unemployment differential	Absolute value of the county-pair difference in the unemployment rate; in percentage points; source: U.S. Bureau of Labor Statistics.
Same state	Binary variable equal to 1 if source and destination county are located in the same state; source: NBER's county distance database.

(*table continued on next page*)

Table 2.A.1 - *continued*

Variable name	Description
Instrumental variables	
Historical travel costs	Costs of traveling from source to destination county in 1920; source: Donaldson and Hornbeck (2016).
Relative Facebook county rank	The sum of the order (rank) in which Facebook became available in the source county and the destination county, divided by the sum of the student population in both counties (see Section 2.4.1.1 and Equation 2.7); source: own calculation and U.S. Census Bureau.
Same highway	Binary variable equal to 1 if source and destination county are connected by the same highway; source: Baum-Snow (2007).
Years since highway construction	Number of years for which source and destination county have been connected by the same highway; source: Baum-Snow (2007).
Variables at county-pair level used in interaction terms	
Bank size	Natural logarithm of the loan-volume-weighted average balance sheet size of banks that lend from source to destination county; source of total assets data: FDIC.
Borrower's volatility exposure	Destination county's exposure to industry-level output volatility calculated using county's industry shares to weight the U.S.-wide output volatility of industries; source: U.S. Bureau of Economic Analysis.
GDP growth	Destination county's average real GDP growth during the last three years; in %; source: U.S. Bureau of Economic Analysis.
Further variables at county-pair level	
Culture: ethnic ancestry	Index quantifying a county pair's cultural distance based on ethnic ancestries; calculation described in Section 2.3.1; source: own calculation.
Culture: racial origin	Index quantifying a county pair's cultural distance based on racial origins; calculation described in Section 2.3.1; source: own calculation.
Culture: religious beliefs	Index quantifying a county pair's cultural distance based on religious beliefs; calculation described in Section 2.3.1; source: own calculation.
Culture: social environment	Index quantifying a county pair's cultural distance based on social environments; calculation described in Section 2.3.1; source: own calculation.
Cultural heterogeneity	Index quantifying the sum of the "cultural distance" between census tracts in the source county and the "cultural distance" between census tracts in the destination county; source: own calculation.
All modes travel costs	Costs of traveling from source to destination county via the cheapest combination of highways, railroads, and waterways; source: Oak Ridge National Laboratory's National Transportation Center.
Highway travel costs	Costs of traveling from source to destination county via highways; source: Oak Ridge National Laboratory's National Transportation Center.
Physical distance (pop.-weighted centroids)	Great-circle distance in miles based on *population-weighted* county centroids; source: U.S. Census Bureau, own calculation.
Vote-share differential	Absolute difference of the vote share for the Republican candidate during the 2016 presidential election; source: MIT Election Data and Science Lab.
Inverse population product	One over the product of the source and destination county populations; source: U.S. Census Bureau.

(*table continued on next page*)

Table 2.A.1 - *continued*

Additional loan-level data	
Combined LTV	Combined loan-to-value ratio of all mortgages on the borrower's property; in %; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
Delinquent	Indicator variable equal to 1 if the loan is at least 90 days past due; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
DTI	Borrower's debt-to-income ratio; in %; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
FICO score	Borrower's credit score; higher values signal higher creditworthiness; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
Interest rate	Loan's interest rate at the time of origination; in basis points; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
First-time buyer	Indicator variable equal to 1 if the borrower is buying a home for the first time; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
Not in default	Indicator variable equal to 1 if the loan is not in default and not at least 2.5 years past due; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
Original loan amount	Loan amount at the time of origination; enters regressions in logs; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
Unpaid balance	Current amount still owed by the borrower; enters regressions in logs; source: Fannie Mae's and Freddie Mac's Single Family Loan-Level Data Sets.
Additional county-level data for the real-effects analysis	
Social proximity to bank capital	County i's social proximity to bank capital at time t is defined as $\sum_j \mathit{Social\ connectedness}_{i,j} \cdot \mathit{Total\ assets}_{j,t}$; total assets is the sum of total assets of all banks with headquarters in county j; scaled to a standard deviation of 1; sources: Bailey et al. (2018a), FDIC, own calculation.
Physical proximity to bank capital	County i's physical proximity to bank capital at time t is defined as $\sum_j (\mathit{Physical\ distance})^{-1}_{i,j} \cdot \mathit{Total\ assets}_{j,t}$; total assets is the sum of total assets of all banks with headquarters in county j; scaled to a standard deviation of 1; sources: NBER's county distance database, FDIC, own calculation.
Cultural proximity to bank capital	County i's cultural proximity to bank capital at time t is defined as $\sum_j (\mathit{Cultural\ distance})^{-1}_{i,j} \cdot \mathit{Total\ assets}_{j,t}$; total assets is the sum of total assets of all banks with headquarters in county j; scaled to a standard deviation of 1; source: own calculation.
Employment	Number of employed people; enters regressions in logs; source: U.S. Bureau of Labor Statistics.
Real GDP growth	County-level real GDP growth; in %; source: U.S. Bureau of Economic Analyses.
Small-firm percentage	Share of small firms (=less than 20 employees) in the destination county; calculated as the nationwide share of small firms per industry weighted with a county's industry shares; in %; source: U.S. Census Bureau's Statistics of U.S. Businesses.

Table 2.A.2: Measurement of cultural distance: variables, categories, and subcategories

The table lists the variables for the measurement of the cultural distance between counties and associates them with Lieske's (1993) four dimensions of regional subcultures: ethnic ancestry, racial origin, religious beliefs, and the social environment. This environment is further divided into subcategories for weighting purposes. Section 2.3.1 explains the construction of our cultural distance measure in detail.

Cultural distance				
Ethnic ancestry	**Racial origin**	**Religious beliefs**	**Social environment**	
% American	% Asian	% Black Protestant	**Age**	**Mobility**
% British	% black	% Evangelical Protestant	% 19 or younger	% 5 years not moved
% Eastern European	% Hispanic	% Mainline Protestant	% 20 to 29	**Occupation**
% French	% Native American	% Catholic	% 30 to 64	% agriculture
% German	% white	% Mormon	% over 64	% construction
% Greek		% Orthodox	**Education**	% manufacturing
% Irish			% $\geq$ college degree	% service
% Italian			% $<$ high-school diploma	**Population**
% Northern European			**Family**	% urban
% Russian			% two-parent families	% total
% Sub-Saharan African			% females in labor force	**Racial diversity**
			Income inequality	Gini coefficient of
			Gini coefficient	racial origins

2.B Appendix: additional figures and tables

Figure 2.B.1: Marginal effect of social connectedness across time

The figure displays the evolution of the marginal effect of social connectedness on log cross-county loan volumes over time. Social connectedness measures the relative probability that a person in a source county and a person in a destination county are acquainted with each other, measured in percent of the maximum social connectedness between any two U.S. counties. In line with the specification in Table 2.5, column 2, the results are obtained while controlling for source-county-time fixed effects, destination-county-time fixed effects, physical and cultural distances, and the additional macroeconomic control variables. However, unlike in that regression, social connectedness is interacted with indicator variables for each year.

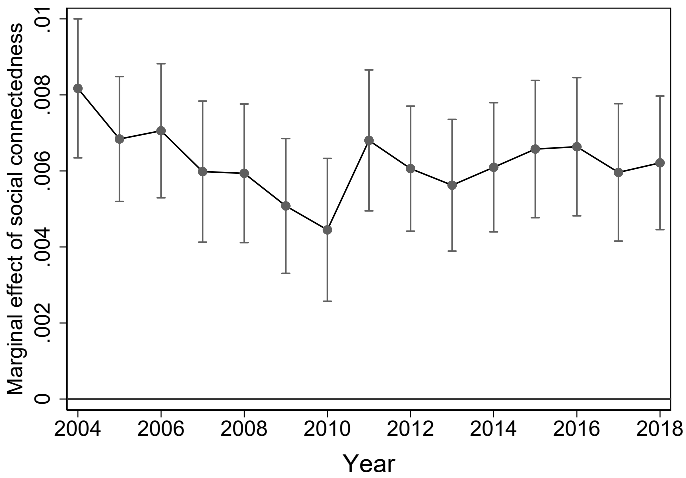


Figure 2.B.2: Marginal effect of social connectedness: information sensitivity of loans

The figures display the marginal effect of social connectedness on log cross-county loan volumes in dependence of the variables indicated below each figure. Social connectedness measures the relative probability that a person in a source county and a person in a destination county are acquainted with each other, measured in percent of the maximum social connectedness between any two U.S. counties. Figures (a) and (b) are based on the estimates reported in Table 2.7, columns 1 and 2. Figures (c) and (d) are based on the estimates reported in Table 2.8, columns 3 and 6. Table 2.A.1 defines the variables. For summary statistics, see Tables 2.1 and 2.B.4.

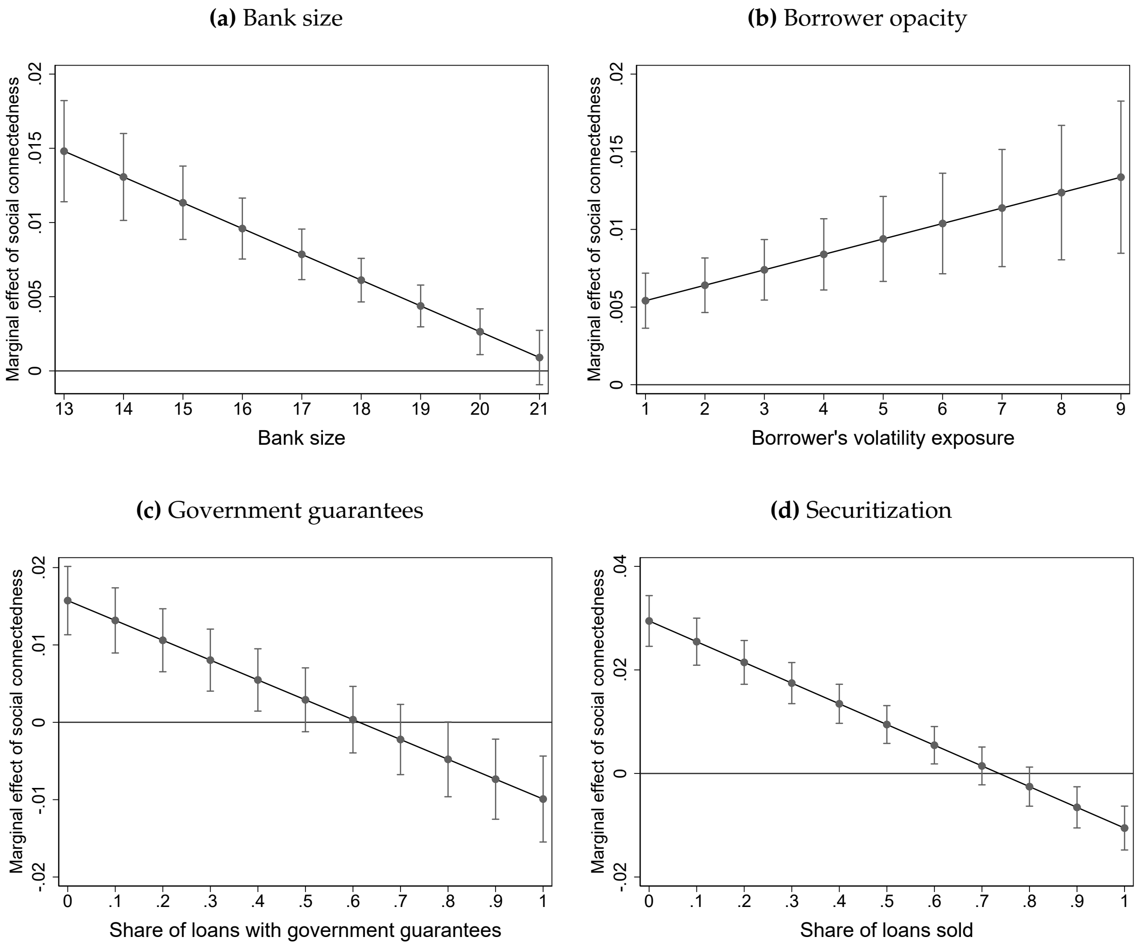


Table 2.B.1: The role of distance and connectedness: alternative clustering

The regressions in this table assess the robustness of our results with respect to alternative approaches to the clustering of standard errors. Column 1 restates our baseline regression reported in column 4 of Table 2.4, where standard errors are clustered at the source and destination county levels. In column 2, standard errors are clustered at the source and destination state levels. Column 3 accounts for the dyadic structure of our data by following the clustering approach in Cameron and Miller (2014). The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties i and j, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain the standard errors. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
Dependent variable:	log(Volume of SME loans)		
Clustering:	Source and destination county	Source and destination state	Dyadic
Social connectedness	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)
Physical distance	-0.269***	-0.269***	-0.269***
	(0.051)	(0.048)	(0.051)
Cultural distance	-0.015**	-0.015**	-0.015**
	(0.007)	(0.006)	(0.007)
Source county FE	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes
No. of obs.	66,684	66,684	66,684
Adj. R^2	0.525	0.525	0.525
Adj. R^2 within	0.132	0.132	0.132

Table 2.B.2: Social connectedness and loan allocations: log-log specification

This table illustrates the robustness of our results with respect to an alternative specification of social connectedness. Throughout the paper, we winsorize social connectedness at the 99^{th} percentile to account for outliers in the distribution and divide it by its maximum value to interpret the variable as the social connectedness in percent of the maximum social connectedness between any two U.S. counties (compare Section 2.3.1). As an alternative specification, this table uses the logarithm of social connectedness without previously winosrizing and rescaling the variable. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 describes these variables in detail. The bottom part of the table informs about the statistical significance of the difference between the coefficients in columns 1 to 3 and those in column 4. The standardized beta coefficients at the end of the table express the effect of a standard-deviation increase in the explanatory variable in standard deviations of the dependent variable. Control variables vary at the county-pair level and consist of the GDP growth and unemployment differentials between the two counties, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.B.5 reports the coefficients of the control variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			
Social connectedness	0.247***			0.146***
	(0.023)			(0.042)
Physical distance		-0.389***		-0.195**
		(0.041)		(0.079)
Cultural distance			-0.034***	-0.010
			(0.007)	(0.007)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes
No. of obs.	66,684	66,684	66,684	66,684
Adj. R^2	0.523	0.522	0.515	0.525
Adj. R^2 within	0.129	0.126	0.114	0.132
P-value for H0: no difference to coefficient in column (4)				
Social connectedness	0.036			
Physical distance		0.03		
Cultural distance			0.01	
Standardized beta coefficients				
Social connectedness	0.3			0.18
Physical distance		-0.25		-0.13
Cultural distance			-0.13	-0.04

Table 2.B.3: Social connectedness and loan allocations: headquarter locations

This table illustrates the robustness of our results with respect to the definition of the source county of loans. Column 1 restates the baseline regression from Table 2.4, column 4, where source counties are based on banks' branch networks. In column 2, we re-estimate our baseline regression but determine source counties based on banks' headquarters. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties i and j, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. The standardized beta coefficients at the end of the table express the effect of a standard-deviation increase in the explanatory variable in standard deviations of the dependent variable. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)
Dependent variable:	log(Volume of SME loans)	
Bank location:	Branch location	Headquarter location
Social connectedness	0.007***	0.012***
	(0.001)	(0.002)
Physical distance	-0.267***	-0.381***
	(0.051)	(0.087)
Cultural distance	-0.016**	-0.027***
	(0.007)	(0.009)
Source county FE	Yes	Yes
Destination county FE	Yes	Yes
County-pair-level control variables	Yes	Yes
No. of obs.	66,684	73,305
Adj. R^2	0.525	0.545
Adj. R^2 within	0.132	0.185
Standardized beta coefficients		
Social connectedness	0.15	0.12
Physical distance	-0.19	-0.17
Cultural distance	-0.09	-0.06

Table 2.B.4: Descriptive statistics: mortgage-lending sample

The table displays descriptive statistics for the county-pair-level mortgage loan sample used to analyze heterogeneities across the information sensitivity of loans in Table 2.8. All variables are at the county-pair level. For instance, "volume of mortgage loans" equals the volume of loans provided by all bank branches in a source county to all borrowers in the destination county. Table 2.A.1 provides variable definitions and data sources.

	N	Mean	Median	SD	Min	Max
Connectedness and distances						
Social connectedness	34,483	33	4	42	0	100
Cultural distance	34,483	14	13	7	0	47
Physical distance [miles]	34,483	452	272	501	5	4,898
log(Physical distance)	34,483	5.4	5.6	1.4	1.6	8.5
Lending data						
Volume of mortgage loans [thousand USD]	34,483	1,559	242	8,667	0	412,072
log(Volume of mortgage loans)	34,483	10.5	12.4	5.2	0.0	19.8
Loans without guarantees [log(Volume of)]	34,483	8.8	12.0	6.1	0.0	19.8
Loans with guarantees [log(Volume of)]	34,483	4.2	0.0	6.1	0.0	18.7
Guaranteed share	34,483	0.2	0.0	0.4	0.0	1.0
Loans kept on book [log(Volume of)]	34,483	4.9	0.0	6.2	0.0	19.3
Loans sold [log(Volume of)]	34,483	7.8	11.9	6.5	0.0	19.7
Sold share	34,483	0.5	0.7	0.5	0.0	1.0
County-pair-level control variables						
Common border	34,483	0.2	0.0	0.4	0.0	1.0
GDP growth differential [ppt.]	34,483	3.2	2.4	3.2	0.0	37.1
Gross trade [million USD]	34,483	68	21	111	0	1,056
Gross migration [%]	34,483	0.06	0.00	0.17	0.00	3.35
Gross commuting [%]	34,483	0.3	0.0	0.9	0.0	16.9
Same state	34,483	0.3	0.0	0.5	0.0	1.0
Unemployment differential [ppt.]	34,483	1.3	1.0	1.2	0.0	20.3

Table 2.B.5: Social connectedness and loan allocations: control variables

The table restates the regressions from Table 2.4 while additionally reporting the coefficients of control variables. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. All further variables in this table also vary at county-pair level. Table 2.A.1 summarizes variable definitions. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)			
Social connectedness	0.012***			0.007***
	(0.001)			(0.001)
Physical distance		-0.389***		-0.267***
		(0.041)		(0.051)
Cultural distance			-0.034***	-0.016**
			(0.007)	(0.007)
Same state	0.339***	0.296***	0.777***	0.107
	(0.070)	(0.084)	(0.072)	(0.069)
Common border	0.774***	0.804***	1.078***	0.655***
	(0.050)	(0.076)	(0.050)	(0.061)
GDP growth differential	-0.008	-0.007	-0.006	-0.006
	(0.007)	(0.008)	(0.008)	(0.008)
Unemployment differential	-0.015	-0.019	-0.007	-0.002
	(0.022)	(0.022)	(0.021)	(0.020)
Gross trade	0.001***	0.000	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Gross commuting	0.089***	0.074***	0.110***	0.082***
	(0.027)	(0.026)	(0.026)	(0.025)
Gross migration	0.252*	0.302**	0.241*	0.204
	(0.132)	(0.129)	(0.134)	(0.135)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
No. of obs.	66,684	66,684	66,684	66,684
Adj. R^2	0.519	0.522	0.515	0.525
Adj. R^2 within	0.121	0.126	0.114	0.132

Table 2.B.6: Social connectedness and loan allocations within and across states

This table analyzes the relationship between bank lending and social connectedness within and across states. Column 1 restates our baseline regression from Table 2.4, column 4. Columns 2 and 3 introduce interactions of social connectedness and the distance measures with the same-state indicator variable. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties i and j, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
Dependent variable:	log(Volume of SME loans)		
Social connectedness	0.007***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)
Social connectedness · Same state		0.003***	0.000
		(0.001)	(0.002)
Physical distance	-0.267***	-0.284***	-0.241***
	(0.051)	(0.053)	(0.057)
Physical distance · Same state			-0.300***
			(0.068)
Cultural distance	-0.016**	-0.016**	-0.021***
	(0.007)	(0.007)	(0.008)
Cultural distance · Same state			0.031***
			(0.008)
Source county FE	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes
No. of obs.	66,684	66,684	66,684
Adj. R^2	0.525	0.525	0.526
Adj. R^2 within	0.132	0.132	0.135

Table 2.B.7: Social connectedness and the probability of bank lending at shorter distances

Columns 1 and 3 restate the regressions from Table 2.5, columns 4 and 5. Columns 2 and 4 re-estimate the same specification but restrict the sample to county pairs that are closer to each other than the median distance between counties in the United States, 776 miles, as banks rarely lend across longer distances. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties i and j, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	log(Volume of SME loans)		Lending indicator	
Maximum distance between county pairs:	Unrestricted	776 miles	Unrestricted	776 miles
Social connectedness	0.0033***	0.0029***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Physical distance	-0.1432***	-0.2373***	-0.0078***	-0.0128***
	(0.013)	(0.018)	(0.001)	(0.001)
Cultural distance	-0.0042***	-0.0062***	-0.0002**	-0.0003***
	(0.001)	(0.002)	(0.000)	(0.000)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes	Yes
No. of obs.	9,526,482	4,763,196	9,526,482	4,763,196
Adj. R^2	0.337	0.299	0.332	0.297
Adj. R^2 within	0.077	0.092	0.068	0.082

Table 2.B.8: Instrumental variable approaches: first-stage regressions

This table reports the first-stage regressions of the instrumental-variable estimates reported in Table 2.6. The dependent variable, *social connectedness*$_{i,j}$, quantifies the relative probability that a person in county *i* and a person in county *j* are acquainted with each other, measured in percent of the maximum social connectedness between any two U.S. counties. *Same highway*$_{i,j}$ is an indicator variable that equals one if two counties are connected by the same highway. *Years since highway construction*$_{i,j}$ counts the number of years that have passed since two counties have been connected by the same highway. *Historical travel costs*$_{i,j}$ is an index of county-to-county travel costs in 1920. The *relative Facebook county rank*$_{i,j}$ is defined as $(Rank_i + Rank_j)/(Student\ population_i + Student\ population_j)$, where $Rank_i$ $(Rank_j)$ is the rank number of county *i* (*j*) based on the order in which Facebook appeared across counties. *Physical distance*$_{i,j}$ refers to the logarithm of the distance between counties *i* and *j* in miles. *Cultural distance*$_{i,j}$ is an index that measures the cultural distance between counties *i* and *j* in percent of the maximum cultural distance between any two U.S. counties. Table 2.A.1 summarizes variable definitions. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	Social connectedness			
Same highway	3.783***			
	(0.518)			
Years since highway construction		0.071***		
		(0.010)		
Historical travel costs			4.328***	
			(0.377)	
Relative Facebook county rank				163.117***
				(13.265)
Physical distance	-12.338***	-12.291***	-13.487***	-15.344***
	(1.580)	(1.579)	(1.466)	(0.939)
Cultural distance	-0.434***	-0.433***	-0.378***	-0.769***
	(0.053)	(0.053)	(0.055)	(0.073)
Same state	27.519***	27.521***	22.623***	26.351***
	(1.843)	(1.843)	(1.463)	(1.691)
Common border	20.717***	20.726***	13.235***	13.532***
	(1.288)	(1.288)	(1.302)	(1.346)
GDP growth differential	0.009	0.009	-0.064	0.009
	(0.065)	(0.065)	(0.048)	(0.086)
Unemployment differential	-0.734***	-0.733***	-0.635***	-0.698***
	(0.213)	(0.213)	(0.173)	(0.218)
Gross trade	-0.004	-0.004	-0.004	0.011***
	(0.003)	(0.003)	(0.003)	(0.004)
Gross commuting	0.019	0.036	-1.443***	-7.314***
	(0.377)	(0.377)	(0.375)	(0.911)
Gross migration	5.565***	5.575***	5.281***	5.331
	(1.935)	(1.938)	(1.995)	(6.011)
Present-day travel costs	1.285	1.226	-13.236***	
	(1.715)	(1.712)	(1.791)	
Population control				-0.000***
				(0.000)
Source county FE	Yes	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes	Yes
No. of obs.	66,647	66,647	56,223	56,852
Adj. R^2	0.858	0.858	0.882	0.814
Adj. R^2 within	0.674	0.674	0.734	0.535

Table 2.B.9: Instrumental variable approaches: alternative specifications

This table provides robustness checks for our instrumental variable approaches. Columns 1 and 2 re-estimate the instrumental-variable regressions reported in columns 1 and 2 of Table 2.6 while excluding counties in which the share of the population that lives in urban areas exceeds the 75^{th} percentile of its distribution. The instrument in column 1, $same\ highway_{i,j}$, is an indicator variable that equals one if counties i and j are connected by the same highway. $Years\ since\ construction_{i,j}$, the instrument in column 2, equals the number of years for which counties i and j have been connected by the same highway. In column 3, we repeat our instrumental variable regression based on the initial Facebook rollout, but use *relative* social connectedness instead of the absolute measure in Table 2.6, column 4. $Facebook\ rollout_{i,j}$ (column 3) is an index that relies on the order in which Facebook became available in counties i and j. The dependent variable, $log(volume\ of\ SME\ loans)_{i,j}$, is the logarithm of the total volume of all loans from banks in county i to small and medium-sized enterprises in county j. $Social\ connectedness_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. $Physical\ distance_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. $Cultural\ distance_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)
Dependent variable:	log(Volume of SME loans)		
Instrument:	Same highway	Years since construction	Facebook rollout
Social connectedness	0.034***	0.037***	0.128*
	(0.013)	(0.014)	(0.076)
Physical distance	-0.252	-0.223	0.861
	(0.163)	(0.170)	(0.687)
Cultural distance	-0.002	-0.001	0.045
	(0.009)	(0.009)	(0.035)
Source county FE	Yes	Yes	Yes
Destination county FE	Yes	Yes	Yes
County-pair-level control variables	Yes	Yes	Yes
Present-day travel costs	Yes	Yes	No
No. of obs.	49,725	49,725	56,852
Adj. R^2	0.485	0.478	-0.010
Adj. R^2 within	0.083	0.069	-0.944
Instrument (1st stage)	3.427***	0.064***	16.778***
	(0.000)	(0.000)	(0.001)
F-value (1st stage)	41.241	37.386	10.6

Table 2.B.10: Social connectedness and loan allocations: SME loans vs. mortgage loans

This table compares our baseline estimates obtained based on the sample of cross-county loans to small and medium-sized enterprises with the corresponding estimates based on the mortgage-loan sample. Column 1 restates our baseline regression reported in column 4 of Table 2.4. Column 2 reports the results for the mortgage loan sample. The standardized beta coefficients at the end of the table allow a meaningful comparison of the size of the estimates as they express the effect of a standard-deviation increase in the explanatory variable in standard deviations of the dependent variable. *Social connectedness*$_{i,j}$ quantifies the relative probability that a person in county i and a person in county j are acquainted with each other, measured in percent of the maximum social connectedness between any two counties in the United States. *Physical distance*$_{i,j}$ refers to the logarithm of the distance between counties i and j in miles. *Cultural distance*$_{i,j}$ is an index that measures the cultural distance between counties i and j in percent of the maximum cultural distance between any two U.S. counties. Section 2.3.1 discusses these variables in detail. Control variables also vary at the county-pair level and consist of the GDP growth and unemployment differentials between counties i and j, gross migration and trade, the share of the commuting population, as well as same state and common border indicator variables. Table 2.A.1 defines the variables. The parentheses contain standard errors clustered at the source county and destination county levels. ***, **, * indicate significance at the 1%, 5%, and 10% levels.

Dep. var.: log(Volume of ...)	(1) SME loans	(2) Mortgage loans
Social connectedness	0.007***	0.009***
	(0.001)	(0.003)
Physical distance	-0.267***	-0.462***
	(0.051)	(0.109)
Cultural distance	-0.016**	-0.037**
	(0.007)	(0.015)
Source county FE	Yes	Yes
Destination county FE	Yes	Yes
County-pair-level control variables	Yes	Yes
No. of obs.	66,684	34,483
Adj. R^2	0.525	0.157
Adj. R^2 within	0.132	0.051
Standardized beta coefficients		
Social connectedness	0.12	0.07
Physical distance	-0.17	-0.12
Cultural distance	-0.06	-0.05

Chapter 3

Asset Price Bubbles and Systemic Risk*

Abstract: This chapter analyzes the relationship between asset price bubbles and systemic risk, using bank-level data covering almost thirty years. Systemic risk of banks rises already during a bubble's build-up phase, and even more so during its bust. The increase differs strongly across banks and bubble episodes. It depends on bank characteristics (especially bank size) and bubble characteristics, and it can become very large: In a median real estate bust, systemic risk increases by almost 70 percent of the median for banks with unfavorable characteristics. These results emphasize the importance of bank-level factors for the build-up of financial fragility during bubble episodes.

3.1 Introduction

Financial crises are often accompanied by a boom and bust cycle in asset prices (Borio and Lowe, 2002; Kindleberger and Aliber, 2005). Bursting asset price bubbles can have detrimental effects on the financial system and give rise to systemic financial crises. Yet, not all

*This chapter is based on a paper published as: Brunnermeier, Markus; Rother, Simon; Schnabel, Isabel (2020): Asset Price Bubbles and Systemic Risk. Review of Financial Studies 33 (9), pp. 4272–4317. DOI: 10.1093/rfs/hhaa011. We thank Itay Goldstein (the Editor), three anonymous referees, our discussants Kerstin Bernoth, Kristina Bluwstein, Andrei Dubovik, Simon Gilchrist, Carolin Holzmann, Erik Lüders, Alberto Martin-Utrera, Alan Moreira, Deyan Radev, and Melanie Schienle for valuable comments and suggestions. We also thank Mark Carlson, Hans Degryse, Florian Heider, Vasso Ioannidou, Markus Pelger, Enrico Perotti, Farzad Saidi, Ulrich Schüwer, Sascha Steffen, Stefan Zeume, and participants of the Spring Meeting of Young Economists in Halle, the 6^{th} Research Workshop in Financial Economics in Bonn, the FIRM Research Conferences in Frankfurt and Mainz, the annual meeting of the Verein für Socialpolitik in Wien, the 9^{th} European Banking Center Network Conference in Lancaster, the Wharton Conference on Liquidity and Financial Fragility in Philadelphia, the Workshop on Bubbles in Macroeconomics in Barcelona, the Conference "Women in Macroeconomics and Finance" in Cologne, the Conference on the Real Effects of Financial Crises: Past, Present, Future in Frankfurt, the 2^{nd}CRC TR 224 Workshop in Montabaur, and the Annual Meeting of the American Finance Association in Philadelphia, as well as seminar participants at the CPB in Den Haag and Bonn University for valuable feedback. Financial support from the Frankfurt Institute for Risk Management and Regulation (FIRM) and from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (Project C04) and through EXC 2126/1-390838866 under Germany's Excellence Strategy is gratefully acknowledged.

bubbles are equally harmful. Some, like the one preceding the global financial crisis, contribute to the collapse of the entire financial system, while others, like the dotcom bubble, cause high financial losses without any wider macroeconomic consequences.

Historical evidence suggests that the severity of crises after the burst of a bubble depends on the state of the financial system. Bubbles accompanied by strong lending booms tend to be followed by more severe crises (Jordà, Schularick, and Taylor, 2015b; Brunnermeier and Schnabel, 2016). Moreover, disturbances may be amplified through the financial sector. For example, the US subprime mortgage market accounted for only 4 percent of the total US mortgage market at the time of the burst of the subprime bubble (Brunnermeier and Oehmke, 2013, p. 1223). Yet, this burst gave rise to one of the largest financial crises in history, because the initial shock was amplified by the imbalances that had built up in the financial sector.

While the impact of asset price bubbles on macroeconomic variables is well-documented (Jordà, Schularick, and Taylor, 2013, 2015a, 2015b), little is known about the role of individual financial institutions in the build-up of systemic risk during asset price bubbles. However, this knowledge is crucial to understand the channels through which asset price bubbles affect systemic risk and to design appropriate policy responses. Moreover, there are numerous historical examples where a single systemically important financial institution has played a critical role in a financial crisis, just like Lehman Brothers did. Hence, not only the overall size of financial sector imbalances during asset price bubbles matters but also the allocation of risks across banks.

In order to fill this gap in the literature, we empirically analyze the relationship between asset price bubbles and systemic risk at bank level. Our analysis covers stock market and real estate bubbles in 17 countries over almost thirty years, focusing on the role of banks' size, loan growth, leverage, and maturity mismatch. Moreover, we analyze the role of bubble characteristics, namely their length and size.

Measuring systemic risk at bank level yields additional insights to employing a binary indicator of financial crises. First, it allows to analyze changes in systemic risk across banks during asset price bubbles in addition to the aggregate level of systemic risk. This is important because financial crises are often not merely the result of macroeconomic shocks but are reinforced by contagion effects within the financial sector, for which a small number of banks often play an important role. The heterogeneity across banks has implications for regulation: It yields information on which banks exhibit particularly strong increases in systemic risk during bubble episodes and thus deserve increased regulatory and supervisory attention. Second, using continuous measures of systemic risk raises the statistical power of our estimates due to their variation over time and across banks, whereas banking crises are rare events. Third, systemic risk measures are useful from a conceptual perspective. Unlike a financial crisis dummy, they also account for episodes of financial fragility that did not result in a crisis. In fact, increased systemic risk predicts future declines in real activity (Allen, Bali, and Tang, 2012; Engle, Jondeau, and Rockinger, 2015; Giglio, Kelly, and Pruitt, 2016; Brownlees and Engle, 2017). This points to costs of financial fragility independent of whether the risks materialize. Hence, regulation should care about episodes of high systemic risk due to their crisis potential and the real effects of financial fragility.

Our analysis is based on a broad, bank-level dataset spanning the time period from 1987 to 2015. The dataset contains monthly observations on 1,264 financial institutions. The empirical analysis models banks' contributions to systemic risk, or banks' exposures to systemic risk, as a function of financial bubbles as well as bank- and country-level characteristics. Our analysis distinguishes between the boom and bust phases of bubble episodes to analyze both the build-up of asset price bubbles as well as their bursting. We allow the effect of bubbles to depend on bank characteristics (bank size, loan growth, leverage, maturity mismatch) and on bubble characteristics (boom and bust length and size) to account for the heterogeneity across banks and bubble episodes.

The key challenges for our analysis are twofold. First, we need to identify bubble episodes. Asset price bubbles followed by deep turmoil when bursting have attracted most attention in the literature. Relying on such bubbles could, however, lead us to overestimate the relationship between asset price bubbles and systemic risk. To prevent this sample selection bias, we instead estimate bubble episodes by applying the Backward Sup Augmented Dickey-Fuller (BSADF) approach introduced by Phillips, Shi, and Yu (2015a, 2015b). This approach identifies bubble episodes based on episodes of non-stationary behavior in price data. We also consider price-to-rent and price-to-dividend data to account for fundamentals.

Additionally, we apply an alternative bubble identification approach proposed by Jordà, Schularick, and Taylor (2015b), which relies on price deviations from trends.

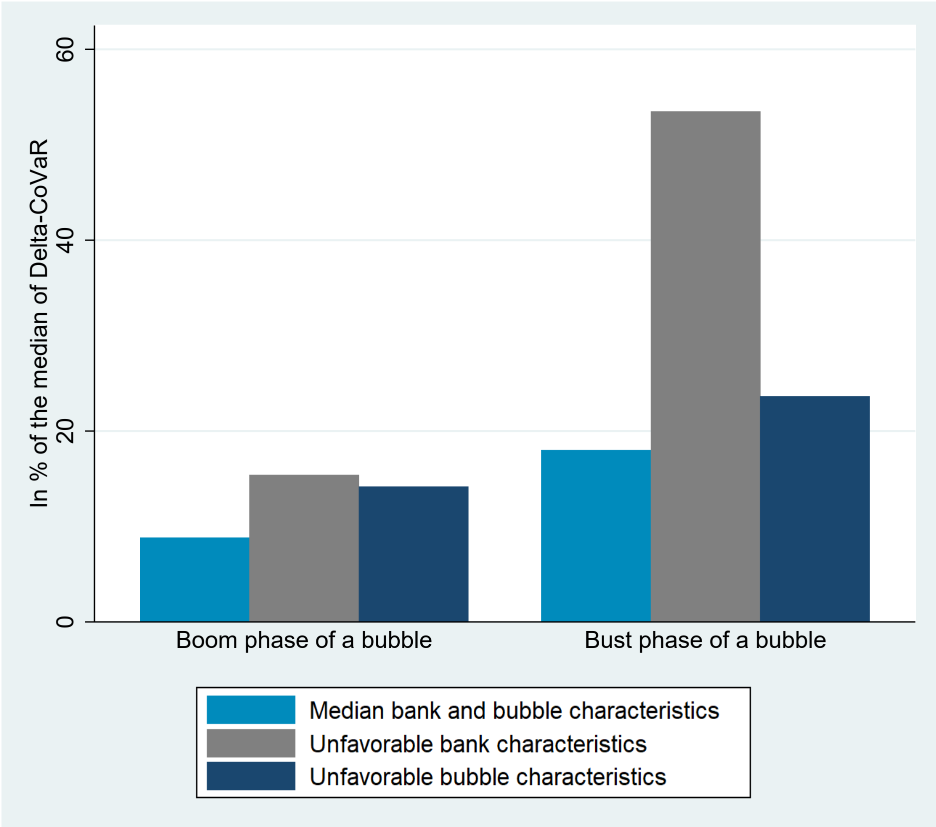
The second challenge lies in the quantification of systemic risk at bank level. We apply the conditional value at risk (ΔCoVaR) introduced by Adrian and Brunnermeier, 2016 and the marginal expected shortfall (MES) proposed by Acharya et al., 2017. Both measures quantify systemic risk at bank level, while taking a complementary perspective. ΔCoVaR quantifies the contribution of a financial institution to the overall level of systemic risk by estimating the additional value at risk (VaR) of the entire financial system when this institution experiences distress. Hence, this measure thinks of banks as *risk inducers*. Contrary to this perspective, MES treats banks as *risk recipients* by calculating the equity losses of a bank conditional on the financial system experiencing distress.

Our results are in line with the common conjecture that asset price bubbles pose a threat to financial stability. As summarized in Figure 3.1, asset price bubbles of median length and size go along with a significant yet moderate increase in systemic risk for banks of median size, loan growth, leverage, and maturity mismatch (light blue bars). This increase in systemic risk is not limited to the turmoil following the burst of a bubble, but exists already during its build-up phase. However, the increase in systemic risk is much larger for banks with unfavorable characteristics (grey bars) and also for bubbles with unfavorable characteristics (dark blue bars). During the bust phase of a bubble with median characteristics, the systemic risk contribution of a bank with unfavorable bank characteristics is almost three times as large as for a bank with median characteristics.

This heterogeneity is mostly driven by bank size, which is the most important determinant of the increase in systemic risk during asset price bubbles. This underlines large banks' potential to propagate and amplify shocks from a bursting asset price bubble when getting under distress. An exception are real estate booms when systemic risk of small banks tends to rise relative to large banks, which may be driven by their stronger focus on mortgage lending. High loan growth and a large maturity mismatch also contribute to a larger increase in systemic risk, but to a smaller extent. The findings regarding leverage are mixed and economically small. With respect to bubble characteristics, we find longer and larger bubbles to be associated with larger increases in systemic risk during the boom phase. During the bust phase, the increase in systemic risk is smaller the more time has passed since

Figure 3.1: The increase in systemic risk during bubble episodes

The figure illustrates the increase in systemic risk during bubble episodes in dependence of bank and bubble characteristics. "Unfavorable characteristics" refers to the 95^{th} percentile of this increase based on the distribution of bank or bubble characteristics as indicated in the legend. The pattern is robust to the choice of the percentile. The figure relies on regression results provided and discussed in Section 3.4.



the burst and the more the bubble has deflated already. This points towards a fading out of the effects of bursting bubbles.

The increase in systemic risk is largest during real estate busts, especially in case of unfavorable bank characteristics: The 95^{th} percentile of the increase in systemic risk in dependence of bank characteristics amounts to 55 percent of the median of ΔCoVaR, the 99^{th} percentile to almost 70 percent. To further put the size of the effect into perspective, consider the most prominent example of a single bank's distress translating into a worldwide systemic financial crisis, namely the collapse of Lehman Brothers. Shortly before its collapse during the bust phase of the US subprime housing bubble in 2008, our estimates imply that systemic risk associated with Lehman getting under distress would have been 40 percent lower if there had not been a bubble. While the risks associated with stock market bubbles are smaller, the estimated increase in systemic risk during these episodes suggests that stock market bubbles should not be disregarded either as a potential source of financial fragility. Complementary analyses shows that aggregate systemic risk increases strongly during bubble episodes, which is in line with the sizeable increases of banks with unfavorable characteristics.

In order to check the robustness of our results, we apply alternative measures of asset price bubbles and systemic risk. Specifically, we normalize price series by rents and dividends, respectively, in the BSADF test. In addition, we identify bubble episodes based on deviations of prices from trends. As a second measure of systemic risk, we use MES to capture banks' exposures to systemic risk. While the results on real estate booms are weaker for banks with median bank characteristics in some regressions, the robustness checks confirm the rise in systemic risk during bubble episodes in case of unfavorable bank or bubble characteristics. For MES, the relationship to specific bank characteristics during some bubble episodes is different from ΔCoVaR in line with the conceptual differences, but the overall relationship between bubbles and systemic risk is again similar, with a strong role for bubble and bank characteristics, especially bank size.

When accounting for a potentially mechanical correlation between our bubble and systemic risk measures, we find that systemic risk increases less during stock market bubbles in some specifications. Distinguishing between banks of different sizes, we show that large banks are more strongly affected during real estate busts as well as booms and busts of stock market bubbles. During real estate booms, systemic risk increases more for small banks, which may be due to their stronger focus on mortgage lending. However, large banks still show a higher level of systemic risk. Moreover, neither a certain country nor a specific time period is driving our main result that increases in systemic risk differ systematically across banks and bubble episodes. Finally, accounting better for business cycles does not affect our main findings.

Overall, our results suggest that strengthening the resilience of the financial system at the bank level may significantly decrease the system's vulnerability to asset price bubbles. Moreover, it seems advisable to try to counteract bubbles early on in order to prevent the build-up of risk in the first place, as longer and larger bubbles tend to increase systemic risk more. An early intervention may lead to smaller costs than "cleaning up the mess" only after a bubble has burst.

The paper proceeds as follows. We start with a brief discussion of the related literature and our contribution in Section 3.2. Section 3.3 elaborates on the data, the identification of bubble episodes, the estimation of systemic risk measures, as well as the empirical model. Section 3.4 contains our baseline results, followed by a discussion of the results using alternative measures in Section 3.5. Section 3.6 presents further robustness checks. We conclude with a discussion of policy implications in Section 3.7. An appendix provides further details on the data, estimation procedures, as well as additional figures and tables.

3.2 Contribution to the literature

Our paper contributes to the literature in macroeconomics and finance studying asset price bubbles, systemic risk, and financial crises. Historically, financial crises have frequently been accompanied by a boom and bust of asset prices in both developed and developing economies. Although the corresponding narrative has been known for a long time (Minsky, 1982), the relationship between asset price bubbles and systemic risk has hardly been analyzed empirically. Historical accounts of prominent financial bubbles have been given, among others, by Shiller (2000), Garber (2000), Kindleberger and Aliber (2005), Allen and Gale (2007), Reinhart and Rogoff (2009), as well as Brunnermeier and Schnabel (2016). Our paper speaks to this literature by analyzing a large number of asset price bubbles, based on a broad set of countries and a time period of almost thirty years. It thus complements this literature by providing an econometric perspective.

The concept of systemic risk appeared in the late 1990s and early 2000s, giving rise to a large literature attempting to measure systemic risk at bank and system level, including Acharya, Engle, and Richardson (2012), Adrian and Brunnermeier (2016), Brownlees and Engle (2017), as well as Acharya et al. (2017). An early literature review is provided by de Bandt and Hartmann (2000). Bisias et al. (2012) provide a taxonomy and discuss the advantages and drawbacks of different approaches. Allen, Babus, and Carletti (2012) as well as Brunnermeier and Oehmke (2013) provide comprehensive reviews, also including the theoretical literature. We draw upon this literature by employing established measures of systemic risk and analyzing asset price bubbles as a new driver of these measures. We also shed light on the interplay between asset price bubbles and bank characteristics that have been shown to be linked to systemic risk, such as bank size, loan growth, leverage, and maturity mismatch.

Similarly, we build on the literature dealing with the identification of asset price bubbles by applying some of the most prominent approaches. Many strategies are built around tests for non-stationary behavior in price data (Kim, 2000; Kim and Amador, 2002; Busetti and Taylor, 2004; Breitung and Homm, 2012).[1] One of the most prominent estimation procedures is the Backward Sup Augmented Dickey-Fuller (BSADF) approach introduced by Phillips, Shi, and Yu (2015a, 2015b) and developed further by Phillips and Shi (2018). The quantitative procedures allow to objectify the classifications. This reduces the selection bias inherent in historical accounts of bubbles and financial crises, which tend to focus on the most severe events, because these were most likely to be reported. We contribute to this literature by contrasting the results of the applications of several conceptually different measures in our analysis of the relationship between the identified bubble episodes and systemic risk.

We also draw on the theoretical literature suggesting channels through which asset price bubbles may give rise to financial instability. Bursting asset price bubbles can set in motion loss and liquidity spirals, forcing distressed institutions to sell assets, thereby further depressing prices and forcing additional asset sales. Through such dynamics, systemic risk may spread well beyond the institutions affected by the initial shock. Brunnermeier (2009), Hellwig (2009) as well as Shleifer and Vishny (2011) argue that it is exactly such dynamics that make risk systemic. Moreover, already Bernanke and Gertler (1989) as well as Bernanke, Gertler, and Gilchrist (1999) pointed out that consequences of losses in net worth are usually long-lasting. Loss and liquidity spirals are the subject of a large literature, including Shleifer and Vishny (1992, 1997, 2011), Allen and Gale (1994), Kiyotaki and Moore (1997, 2005), Xiong (2001), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Acharya, Gale, and Yorulmazer (2011), Acharya and Viswanathan (2011), Diamond and Rajan (2011), as well as Brunnermeier and Sannikov (2014).[2] However, asset price bubbles may not only trigger the materialization of financial imbalances. They can also cause the build-up of these imbalances in the first place. Rising prices increase the value of borrowers' collateral (Bernanke

[1] Early contributions were Shiller (1981), LeRoy and Porter (1981), West's (1987) two-step tests, integration and co-integration based tests as proposed by Diba and Grossman (1988), and tests for intrinsic bubbles as in Froot and Obstfeld (1991). See Gürkaynak (2008) for a discussion of these approaches.

[2] Empirical evidence on such spirals is provided, for example, by Schnabel and Shin (2004), Adrian and Shin (2010), and Gorton and Metrick (2012).

and Gertler, 1989) and the liquidity of assets (Kiyotaki and Moore, 2005), causing banks to increase lending and reduce precautionary liquidity holdings. If the increases in asset prices are due to a bubble, the increased lending might turn out to be excessive and liquidity provisions may prove insufficient. Shin (2008) models demand-side and supply-side effects of asset prices on banks' balance sheets and analyzes the ensuing effects on financial institutions' risk. To capture the role of asset price bubbles both in the build-up and in the realization of financial risks, we consider the emergence of systemic risk in the boom phase as well as the materialization of risk in the bust phase of the bubble.

The comparably small literature looking specifically at the relationship between asset price bubbles and systemic risk has largely taken a macroeconomic perspective. Gertler and Gilchrist (2018) describe how the recent theoretical and empirical literature can explain the developments during the Great Recession. They also provide an empirical analysis, emphasizing the importance of the disruption of financial intermediation relative to other contributing factors. Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2015a, 2015b) provide econometric analyses of the impact of asset price bubbles on the likelihood and costliness of financial crises using long-run historical data. Another broad strand of the literature deals with the role of monetary policy for the development of asset price bubbles and financial stability (see, for example, Bordo and Jeanne, 2002; Galí, 2014; Galí and Gambetti, 2015; Brunnermeier and Schnabel, 2016). By considering the role of bank characteristics for the relationship between asset price bubbles and systemic risk, this paper takes the analysis of bubbles from the macroeconomic to the microeconomic level while maintaining a systemic perspective through its approach to the measurement of risk. This yields new insights on the transmission channels between asset price bubbles and systemic risk and highlights the heterogeneity of the increase in systemic risk across banks.

3.3 Data and empirical model

3.3.1 Data sources and sample

Our analysis relies on the data sources listed in Table 3.C.1 in the Appendix, which also provides variable definitions. The estimation of real estate bubbles is based on real house prices and rents provided by the OECD. Stock market bubbles are estimated using country-specific MSCI price indices and dividends recovered from MSCI return indices from Thomson Reuters' Datastream. These indices were chosen due to their broad coverage (85% of each country's total stock market capitalization) and the unified methodological framework, which makes them comparable across countries. For the estimation of systemic risk, we obtain daily information on the number of outstanding shares, stock prices of common equity, and market capitalization from Thomson Reuters' Datastream for all listed financial institutions. This data is also used to calculate financial system returns used in the estimation of ΔCoVaR. The control variables for this estimation are listed in Table 3.B.1 in Appendix 3.B. Bank balance sheet characteristics are taken from Bureau von Dijk's Bankscope. Finally, we use a large number of macroeconomic control variables.

The sample includes all countries for which we have data on both real estate and stock markets. We keep all banks for which balance sheet information and sufficient return data for the estimation of systemic risk contributions are available.[3] The final sample contains a total of 165,149 monthly observations on 1,264 financial institutions located in 17 countries.[4]

3.3.2 Measuring asset price bubbles

In order to identify asset price bubbles, we rely on the Backward Sup Augmented Dickey-Fuller (BSADF) approach by Phillips, Shi, and Yu (2015a, 2015b) and updated by Phillips and Shi (2018), which is well established in the literature.[5] It outperforms comparable approaches in terms of size and power if multiple bubble episodes occur within a dataset, as is shown by the simulations in Breitung and Homm, 2012 and Phillips, Shi, and Yu, 2015a. This property is valuable for our study as the analyzed sample typically covers more than one bubble episode per price series. The BSADF approach applies backward-expanding sequences of Augmented Dickey-Fuller (ADF) tests to subsamples of price data.

[3] We exclude all institutions with fewer than 260 weeks of non-missing equity return losses to ensure convergence of the quantile regressions used during the estimation of systemic risk contributions.

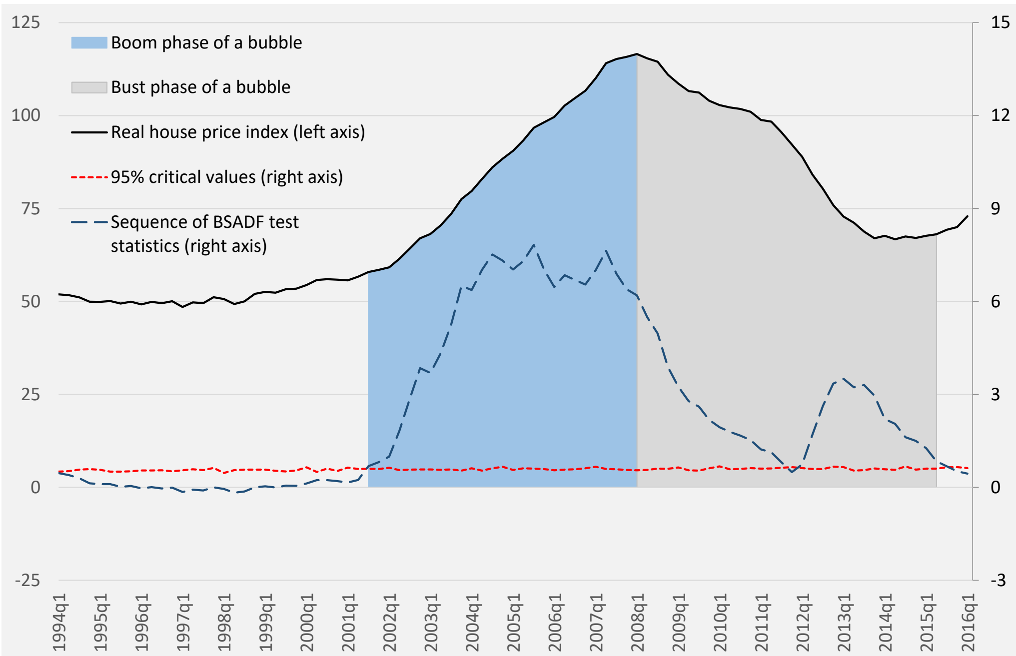
[4] As shown in Table 3.C.2 in the Appendix, the number of banks differs widely across countries. The number of US banks is comparably large due to the high number of small publicly traded banks. This does not drive our results as shown in the robustness check in Section 3.6.2, where we explore differences between large and small banks.

[5] Applications can be found, e. g., in Gutierrez, 2013, Bohl, Kaufmann, and Stephan (2013), Etienne, Irwin, and Garcia (2014), and Jiang, Phillips, and Yu (2015).

Figure 3.2 shows the recent Spanish housing bubble for illustration. The test identifies the beginning of a bubble episode as the point in time at which the sequence of BSADF test statistics (blue dotted line) first exceeds its critical value (red dotted line). It thus signals that the price data (black line) is on an explosive trajectory. The end of a bubble episode is reached once the test statistics fall below their critical values without exceeding it again within a minimum break length. Appendix 3.A provides a detailed description of the estimation procedure.

Figure 3.2: Construction of the bubble indicators

The BSADF approach identifies the beginning of a bubble episode as the point in time at which the sequence of BSADF test statistics (blue dotted line) first exceeds its critical value (red dotted line) and thus signals the price data (black line) being on an explosive trajectory. The end of a bubble episode is reached once the test statistics fall back below their critical values. The approach also applies a minimum (break) length criterion to exclude short blips from being identified as bubbles and to prevent estimating an overly early termination date. Additionally, we distinguish between the boom and the bust phase of a bubble (the blue and grey shaded areas) based on the peak of the price series during each bubble episode. Using this approach, we construct four binary variables for each country, indicating episodes in which a real estate or stock market bubble emerges or collapses. The figure illustrates the construction of these indicators based on the recent Spanish housing bubble. Details on the BSADF approach are provided in Section 3.3.2 and Appendix 3.A.



In alternative specifications, we apply the approach by Jordà, Schularick, and Taylor (2015b) who define a bubble as an episode in which prices are elevated relative to their trend and exhibit a large price correction. Specifically, this approach first identifies episodes of price elevation whenever log real asset prices exceed their Hodrick-Prescott filtered trend by more than one standard deviation. Afterwards, a price correction signal is defined to equal one whenever prices drop by more than 15% within three years. Finally, a bubble is any episode of price elevation during which the price correction signal equals one at least once. As stock prices are more volatile than real estate prices, we increase the threshold of the price correction signal for stock market bubbles by a factor of 3.16, which equals the ratio of the variance of stock prices to real estate prices in our sample. We distinguish between the boom and the bust phases of a bubble (blue and grey shaded areas in Figure 3.2) based on the global peak of the price series during each bubble episode. Hence, we construct four binary variables for each country, indicating episodes in which a real estate or stock market bubble builds up or collapses, in order to capture differences across the phases of the asset price cycle.[6]

We apply the bubble identification approaches to quarterly real house price data covering the period 1976 to 2018, and monthly observations of stock price indices covering the period 1973 to 2018. The data used to estimate the bubble episodes go back further than the data used in the main analysis, which improves the size and power of the BSADF test. Since the real estate data are available only at quarterly frequency while our main analyses are in monthly frequency, the real estate bubble indicators take on the value of the corresponding quarter for each month of the quarter.[7]

Asset price bubbles are often thought of as price deviations from fundamental values. To account for this property, we additionally apply the BSADF approach to normalized price series, i. e., real house prices divided by rents and stock prices divided by dividends. Unfortunately, the availability of rent and dividend data is limited in the time dimension. The advantage of using the normalized price series thus comes at the cost of lower size and power. Our main analyses therefore rely on the BSADF estimates based on non-normalized price series.[8]

The dataset used in the regressions spans the time period from 1987 to 2015. It hence includes not only the US subprime housing bubble, which marks the beginning of the global

[6]The boom-bust distinction introduces a forward-looking component. Our main results are robust towards dropping the boom-bust distinction (see Table 3.C.3).

[7]The results are robust towards using quarterly data (see Table 3.C.4).

[8]The results are very similar when using estimates based on the normalized price series (see Section 3.5.1).

financial crisis, but also many other bubble episodes, such as the dotcom stock market boom and bust around 2000, or the real estate boom and bust cycles around 1990 in several countries.[9] Panel A of Table 3.1 provides an overview of the number of bubble episodes resulting from the three different estimation strategies. According to the BSADF approach, our sample comprises 33 real estate booms and 26 busts, while it contains 45 stock market booms and 47 busts.[10] On average, countries experienced 1.9 real estate booms, 1.5 real estate busts, 2.6 stock market booms, and 2.8 stock market busts. The two alternative bubble identification strategies also find stock market bubbles to occur more frequently than real estate bubbles. Using normalized data, the BSADF approach finds a lower average number of stock market booms and busts per country (2.1 and 1.6) and an almost identical average number of real estate booms and busts (1.9 and 1.6). The trend-deviation approach finds fewer real estate booms and busts per country (1.2 and 1.3) and a similar number of stock market booms and busts as the BSADF test applied to normalized data (1.6 and 1.6).

Figure 3.3 displays the occurrence of booms and busts per country for our baseline bubble estimates. Many stock market bubble episodes occur around the run-up to the global financial crisis, the dotcom bubble, as well as the mid-1980s.[11] Real estate bubbles appear to be much more persistent, especially since the 2000s when most countries experienced a real estate bubble. According to our estimates, real estate booms last on average five years, while the bust lasts only one year. Stock market booms last on average less than two years, and the busts last only half a year. The shorter lifespan of stock market bubbles is consistent with stock prices moving more quickly than real estate prices. With the exception of the stock market bubbles between 2006 and 2008, the bubble episodes relying on normalized data generally identify similar yet shorter periods. The stock market bubble episodes estimated using deviations from trend are again similar to those identified by the BSADF approach. The largest differences are found for real estate bubbles in the second half of the sample. These occur less frequently and are less persistent compared to the bubbles estimated with

[9] The included countries are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

[10] Table 3.1 reports the number of booms and busts during the sample period of our main analyses (1987–2015). The number of booms and busts can differ if the boom phase of a bubble ends before 1987, but its bust phase ends after 1987. We can identify bubble episodes starting before 1987 since the asset price data used for bubble identification go back as far as 1973. Similarly, the number of booms and busts during our baseline sample can differ if a boom starts before 2015, but the bust occurs only afterwards.

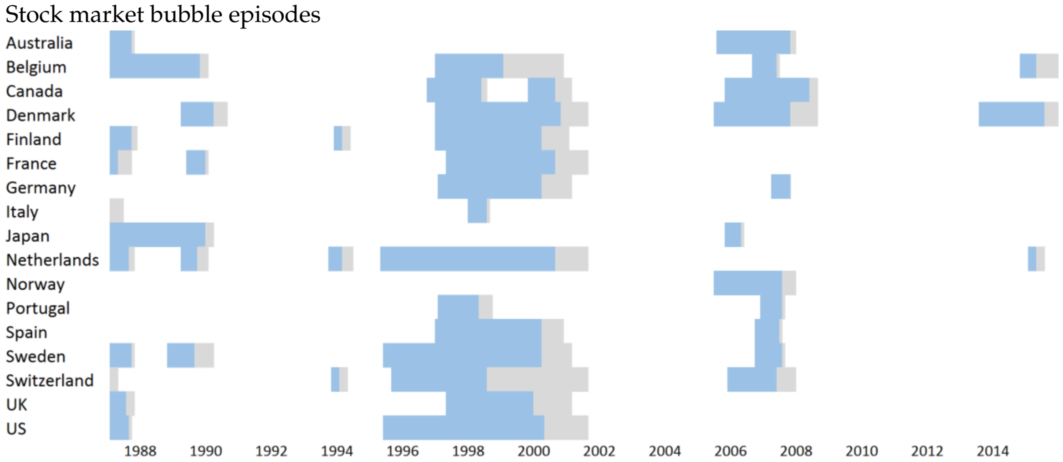
[11] The results are not driven by episodes during which a lot of countries simultaneously experience a stock market bubble (see Table 3.C.5).

the BSADF approach (see Figures 3.C.1 and 3.C.2 in the Appendix). The bubble indicators exhibit a strong positive correlation across the three different identification approaches. For the real estate boom (bust) indicators, the correlations vary between 0.58 and 0.82 (0.44 and 0.77). The correlations of the stock market boom (bust) indicators range between 0.70 and 0.77 (0.57 and 0.87) (see Panel B of Table 3.1).

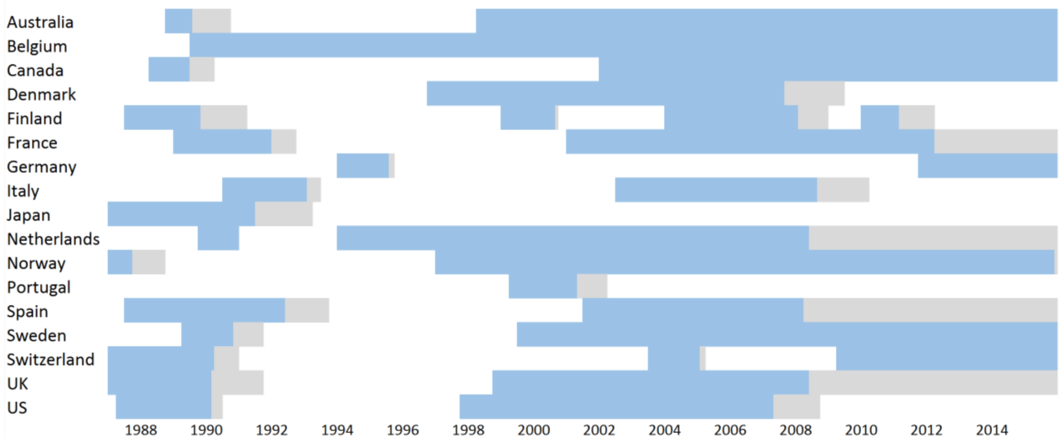
Figure 3.3: Bubble episodes by country and asset class

Periods colored in blue represent the boom phase of an asset price bubble, periods in grey refer to the bust phase of a bubble. Bubble episodes are estimated based on the BSADF approach. For details on the estimation procedure see Section 3.3.2 and Appendix 3.A. The timelines based on the BSADF approach applied to data normalized by fundamentals and the timeline based on the trend-deviation approach are provided in Figures 3.C.1 and 3.C.2.

(a) Stock market bubble episodes



(b) Real estate bubble episodes



On the basis of the estimated bubble episodes, we calculate the bubble characteristics *length* and *size*. *Length* counts the number of months a bubble has been building up since its inception, or that it has been collapsing since its peak. During the boom phase, *size* is the underlying asset's price relative to its pre-bubble level. During the bust, *size* measures the size of the bust (as opposed to the size of the bubble) as the negative of the asset's price relative to the current bubble episode's peak level. *Length* is measured in years while *size* is

Table 3.1: Number of bubble episodes and correlation across bubble measures

The estimation approaches are described in Sections 3.3.2 and Appendix 3.A. The statistics are computed for the dataset used in the baseline regression. Figures 3.3, 3.C.1, and 3.C.2 provide an overview of bubble episodes per country. Differences in the number of booms and busts of bubble episodes are due to bubbles of which only the boom phase, or only the bust phase, takes place during the sample period. We can estimate these bubble episodes since the data used for bubble identification cover a significantly longer time period than the data used in the main analyses (see Section 3.3.2).

Panel A: Number of bubble episodes

	Real estate		**Stock market**	
	Boom	**Bust**	**Boom**	**Bust**
BSADF approach				
Average per country	1.9	1.5	2.6	2.8
Min per country	1	0	1	1
Max per country	4	4	5	5
Total	33	26	45	47
BSADF approach: price-to-rent and price-to-dividend data				
Average per country	1.9	1.6	2.1	1.6
Min per country	0	0	1	0
Max per country	4	4	5	4
Total	33	27	35	27
Trend-deviation approach				
Average per country	1.2	1.3	1.6	1.6
Min per country	0	0	0	0
Max per country	2	2	4	3
Total	21	22	27	27

Panel B: Correlation across bubble indicators resulting from different identification approaches

	BSADF	BSADF normalized	Trend-deviation approach
Real estate boom			
BSADF	1.00		
BSADF normalized	0.82	1.00	
Trend-deviation approach	0.64	0.58	1.00
Real estate bust			
BSADF	1.00		
BSADF normalized	0.44	1.00	
Trend-deviation approach	0.77	0.54	1.00
Stock market boom			
BSADF	1.00		
BSADF normalized	0.77	1.00	
Trend-deviation approach	0.70	0.70	1.00
Stock market bust			
BSADF	1.00		
BSADF normalized	0.60	1.00	
Trend-deviation approach	0.87	0.57	1.00

"BSADF normalized": the BSADF approach applied to price-to-rent and price-to-dividend data.

measured in units of 10 percent. Outside of the respective bubble phases, all *length* and *size* variables are equal to zero.

Table 3.2 displays summary statistics of bubble characteristics during bubble episodes (i. e., conditioning on a bubble being identified). The general patterns are consistent across bubble identification approaches. Real estate bubbles have on average been present for a longer time than stock market bubbles, and booms are more persistent than busts. Stock market booms and busts are on average larger than real estate booms and busts. Finally, the average size of a boom is larger than that of a bust. Specifically, prices are on average 78% above the initial value during a stock market boom, but only 38% during a real estate boom according to our baseline BSADF approach. In a stock market bust, prices are on average 12% below the peak price, while in a real estate bust, prices are only 6% below the peak.

Table 3.2: Descriptive statistics on bubble characteristics during bubble episodes

The statistics are computed for the dataset used in the baseline regression and conditional on the corresponding bubble indicator being equal to one. For example, within stock market boom periods, a stock market boom has on average been present for 29 months ($2.4 \cdot 12$) and features a 78% ($7.8 \cdot 10$) price increase relative to the pre-bubble level according to estimates building on the BSADF approach. Variable definitions are provided in Table 3.C.1. The estimation approaches are described in Sections 3.3.2 and Appendix 3.A.

Variable	Mean	Median	Std. Dev.	5%	95%
BSADF approach					
Real estate boom length [in years]	5.8	5.7	3.3	0.8	10.7
Real estate bust length [in years]	1.2	0.8	1.4	0.1	4.7
Stock boom length [in years]	2.4	2.3	1.5	0.3	4.8
Stock bust length [in years]	0.7	0.7	0.5	0.1	1.3
Real estate boom size [in 10%]	3.8	3.3	2.9	0.3	9.9
Real estate bust size [in 10%]	0.6	0.5	0.7	0.0	1.5
Stock boom size [in 10%]	7.8	7.2	5.4	0.8	15.6
Stock bust size [in 10%]	1.2	1.3	0.8	0.1	2.4
BSADF approach: price-to-rent and price-to-dividend data					
Real estate boom length [in years]	4.5	4.3	3.0	0.7	9.7
Real estate bust length [in years]	1.2	1.1	1.0	0.2	3.2
Stock boom length [in years]	1.7	1.7	1.1	0.2	3.4
Stock bust length [in years]	0.4	0.4	0.2	0.1	0.8
Real estate boom size [in 10%]	2.6	1.8	2.5	0.3	8.1
Real estate bust size [in 10%]	0.4	0.2	0.3	0.0	1.0
Stock boom size [in 10%]	4.3	4.5	2.7	0.6	8.7
Stock bust size [in 10%]	0.6	0.6	0.4	0.0	1.3
Trend-deviation approach					
Real estate boom length [in years]	2.8	2.8	1.6	0.3	5.2
Real estate bust length [in years]	1.1	0.9	1.0	0.2	3.0
Stock boom length [in years]	1.6	1.5	0.9	0.2	2.9
Stock bust length [in years]	0.7	0.8	0.4	0.1	1.3
Real estate boom size [in 10%]	1.9	1.9	1.2	0.3	3.6
Real estate bust size [in 10%]	0.7	0.6	0.5	0.0	1.5
Stock boom size [in 10%]	4.9	4.8	2.6	0.9	8.3
Stock bust size [in 10%]	1.4	1.4	1.0	0.1	2.8

3.3.3 Measuring systemic risk

Our goal is to analyze the link between asset price bubbles and systemic risk at bank level. There exist different approaches to quantify systemic risk at micro level. We rely on two prominent measures, ΔCoVaR (Adrian and Brunnermeier, 2016) and MES (Acharya et al., 2017).[12] A combination of these measures is appealing due to their complementary perspectives. ΔCoVaR regards banks as "risk inducers" and quantifies the contribution of a financial institution to the system's level of systemic risk by estimating the additional value at risk (VaR) of the entire financial system when this institution experiences distress. Contrary to this perspective, MES treats banks as "risk recipients" and calculates the equity losses of a bank conditional on the financial system experiencing distress. While these measures are likely to be correlated, a bank with a high systemic risk exposure does not necessarily also have a high systemic risk contribution, and vice versa.[13] In accordance with the above definition, ΔCoVaR can be written as

$$\Delta CoVaR_q^{system|i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{system|X^i=VaR_{50}^i}, \tag{3.1}$$

where X_i denotes the return loss of institution i and q refers to a percentile of the loss distribution. The VaR is implicitly defined by $Pr(X^i \leq VaR_q^i) = q\%$, and CoVaR is implicitly defined by $Pr(X^{system} \leq CoVaR_q^{system|C(X^i)}|C(X^i)) = q\%$. Following Adrian and Brunnermeier (2016), we estimate ΔCoVaR using quantile regressions, as described in detail in Appendix 3.B.

MES is calculated as the average bank return during the 5% days during which the financial system exhibited the worst losses during the past year.[14] We use overlapping windows

[12] Alternative measures include the Option-iPoD (Capuano, 2008), the DIP (Huang, Zhou, and Zhu, 2009), the measures in Segoviano and Goodhart (2009) as well as in Gray and Jobst (2010), realized systemic risk beta (Hautsch, Schaumburg, and Schienle, 2015), and SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2017).

[13] Consider one bank that lends in the interbank market, and another one that borrows. The lending bank faces counterparty risks and thus has a high systemic risk exposure. At the same time, its systemic risk contribution is low as, in case of a default, its borrowers do not face direct losses and can turn to other funding sources unless the entire interbank market dries up and there is no central bank support. The borrowing bank has a high systemic risk contribution as its default threatens to spread through the interbank market, but its exposure is smaller.

[14] Acharya et al. (2017) use the overall market return instead of the financial system return as a baseline case, but state that relying on the financial system return "maps closer" to the theoretical idea underlying the measure (see their discussion on p. 27). Therefore, we use the financial system index. Results are virtually identical when using the market index (see Table 3.C.6).

to obtain monthly estimates. Denoting the set of trading days with the 5% worst system returns during the past 12 months at month t as $\mathbb{Z}_t^{system}$, MES can be expressed as

$$MES_t^i = \frac{1}{\text{\# of days in } \mathbb{Z}_t} \sum_{\tau \in \mathbb{Z}_t^{system}} X_\tau^i \ . \tag{3.2}$$

Both measures are based on tail correlations of equity returns. As for most other systemic risk measures, the quantified relationship is non-causal. While the measures pick up causal spillovers from one financial institution to the system (or vice versa in case of MES), they also capture correlated shocks that affect many banks at the same time, for example, small banks being "systemic as part of a herd". The common idea underlying tail-correlation measures is that the functioning of the financial system is likely to be impaired if a large number of banks experience distress at the same time. Given this definition of systemic risk, banks' common exposures to shocks are equally relevant for financial stability as spillover risks. The ability of systemic risk measures to capture both sources of systemic risk should hence be considered a virtue rather than a bug.

Table 3.3 provides summary statistics for ΔCoVaR and MES. The mean of ΔCoVaR equals 1.96 so that distress at one institution is associated with an average increase in the financial system's conditional value at risk of 1.96 percentage points based on weekly returns. The mean of MES is 1.34. Hence, on average, a bank's daily equity return was –1.34 percent on days during which the financial system suffered severe market equity value losses.

Figure 3.4 displays the evolution of the average ΔCoVaR and MES in the four considered financial systems (North America, Europe, Japan, and Australia) over time. Both measures evolve similarly. However, ΔCoVaR leads MES due to the use of a rolling window in the estimation of MES. Therefore, in some regressions with MES, we lag all explanatory variables by 6 months. All four financial systems show a marked peak in ΔCoVaR and MES at the time of the global financial crisis.[15] Other times of financial system distress, such as the euro area crisis or the Japanese banking crisis at the beginning of the 1990s, are visible as well. In contrast, the dotcom episode is hardly reflected in the series.

[15]Despite its prominence, this crisis does not drive our results (see Section 3.6.3).

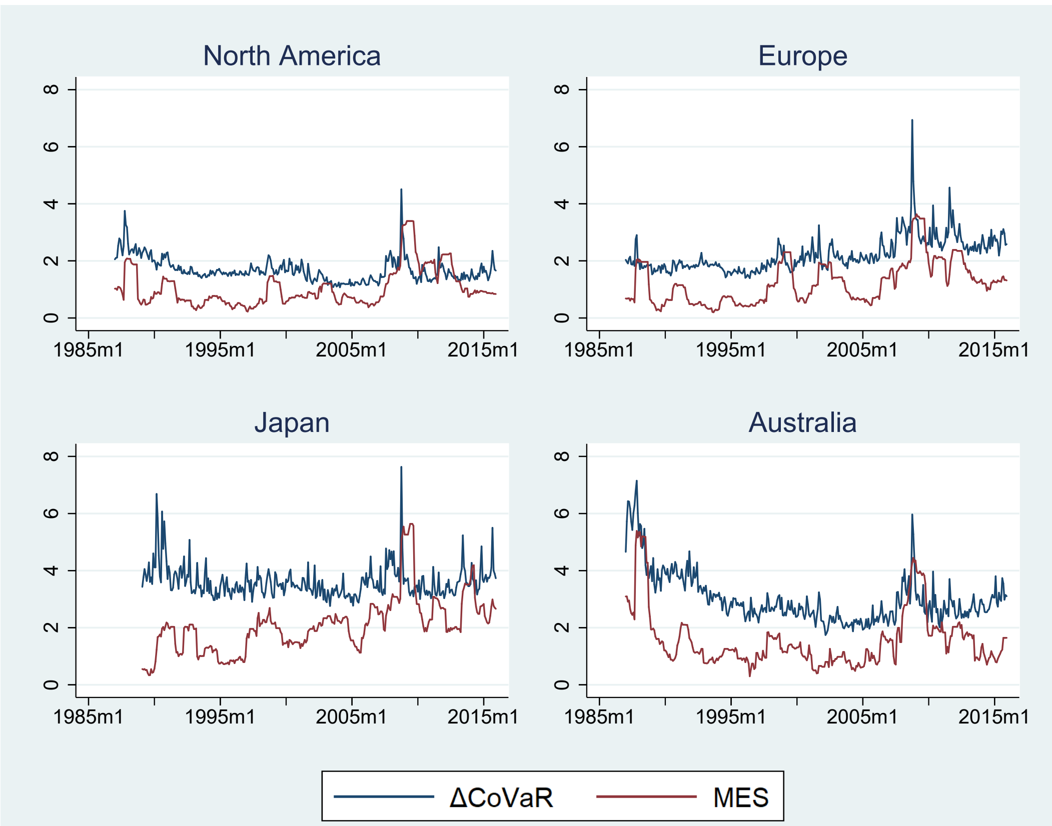
Table 3.3: Descriptive statistics

The statistics are computed for the dataset used in the baseline regression. "Size" and "Interest rate" enter the regressions in logs. "Interest rate" refers to 10-year government bond rates. For descriptive statistics on bubble characteristics see Table 3.2. Variable definitions are provided in Table 3.C.1.

Variable	Mean	Median	Std. Dev.	5%	95%
Dependent variable					
ΔCoVaR	1.96	1.68	1.65	-0.11	4.91
MES	1.34	1.06	1.94	-1.11	4.92
Bank characteristics					
Bank size [billion USD]	64.58	1.88	260.79	0.25	316.73
log(bank size)	1.22	0.63	2.19	-1.40	5.76
Loan growth	0.007	0.006	0.015	-0.012	0.032
Leverage	13.43	11.70	7.14	5.92	27.02
Maturity mismatch	0.69	0.75	0.19	0.27	0.86
Macroeconomic variables					
Banking crisis	0.36	0	0.48	0	1
Real GDP growth	0.021	0.023	0.020	-0.024	0.045
Interest rate	4.70	4.50	1.62	2.52	7.46
log(interest rate)	1.33	1.44	0.51	0.43	1.96
Inflation	0.022	0.021	0.013	-0.002	0.041
Investment-to-GDP growth	-0.004	0.010	0.061	-0.119	0.066

Figure 3.4: Evolution of ΔCoVaR and MES over time

The figure displays the unweighted means of ΔCoVaR and MES in weekly percentage points and daily percent for the four financial systems in our sample: North America, Europe, Japan, and Australia. Details on the estimation procedure of ΔCoVaR and MES are provided in Section 3.3.3 and Appendix 3.B.



3.3.4 Bank-level variables and macroeconomic controls

We include bank characteristics in our analysis that have been shown to drive an institution's systemic risk contribution, such as size (the logarithm of total assets), leverage (total assets divided by equity), and maturity mismatch (short-term liabilities minus short-term assets, divided by total assets). Additionally, we consider the role of loan growth (Δlog(loans)), as credit-fueled bubbles have been shown to be particularly harmful (Jordà, Schularick, and Taylor, 2015b; Brunnermeier and Schnabel, 2016).[16] We apply cubic spline interpolations to obtain monthly observations. The bank-level variables enter the regressions winsorized at the 1- and 99-percent level to deal, for example, with extreme leverage of defaulting institutions and high loan growth of institutions starting from a very low loan level. The median bank in our sample is small with total assets of around 1.9 billion US dollar, and size varies greatly (Table 3.3).[17] Average and median loan growth is close to zero, but our sample contains many observations with high positive and high negative growth rates. The median bank has a leverage of 12 and a median maturity mismatch of 0.75, again with a wide variation.

With respect to macroeconomic control variables, we observe a banking crisis in 36 percent of our sample. Median real GDP growth and inflation are 2.3 and 2.1 percent. The median 10-year government bond rate is 4.5 percent, and median investment-to-GDP growth is slightly positive. Looking at the 5^{th} and 95^{th} percentile of the distribution, we can see that the sample includes severe recessions as well as strong booms, mirroring the diverse macroeconomic developments of the 17 countries over the sample period of almost thirty years.

3.3.5 Empirical model

We regress systemic risk (measured by ΔCoVaR or MES) of institution i at time t on bank fixed effects (α_i), the four binary variables indicating booms and busts in stock and real estate

[16] The literature suggests that bank activities not related to lending may also be relevant (see, e. g., Brunnermeier, Dong, and Palia, 2020). Therefore, we also included the ratio of non-interest rate income to interest rate income in our regressions. However, this variable and its interactions with the bubble indicators are not significant in any regression (see Table 3.C.7) and do not change any coefficient of the other variables significantly. Therefore, we disregard this variable in the remainder of the paper.

[17] In Section 3.6.2, we check whether the link between small and large banks' systemic risk contributions and asset price bubbles differs beyond what is captured by controlling for total assets.

markets ($I_{c,t}^{Bubble}$) in country c at time t, lagged bank characteristics, the interaction terms of the bubble indicators with bank and bubble characteristics, and the lagged country-specific macroeconomic control variables ($C_{c,t-1}$). We do not need to include non-interacted bubble characteristics as they are zero outside of bubble episodes.

$$\begin{aligned} Systemic\ risk_{i,t} = \alpha_i &+ \beta_1 \cdot I_{c,t}^{Bubble} + \gamma \cdot Bank\ characteristics_{i,t-1} \\ &+ \beta_2 \cdot I_{c,t}^{Bubble} \cdot Bank\ characteristics_{i,t-1} \\ &+ \beta_3 \cdot I_{c,t}^{Bubble} \cdot Bubble\ characteristics_{c,t} + \lambda \cdot C_{c,t-1} + u_{i,t}\ . \end{aligned} \tag{3.3}$$

We subtract the median from all bank and bubble characteristics such that the coefficients of the bubble indicators can be interpreted as the change in systemic risk contributions (or exposures) of a bank of *median* size, loan growth, leverage, and maturity mismatch during a boom or bust of *median* size and length. As larger values of ΔCoVaR (MES) correspond to a higher systemic risk contribution (exposure), a positive sign for the coefficients included in β_1 would correspond to an increase in systemic risk during asset price bubbles. The relationship between bubbles and systemic risk is likely to depend on an institution's balance sheet characteristics, which is captured by the coefficients of the respective interaction terms (β_2). We expect a stronger relationship between bubbles and systemic risk for banks with unfavorable bank characteristics. For instance, if a bubble is financed by loans, higher loan growth raises a bank's exposure to the bubble and should thus also imply a higher increase in systemic risk during the bubble. Similarly, the relationship may depend on bubble characteristics, captured by β_3. For example, an emerging asset price bubble might be more harmful the longer it has lasted already because it may feed back into banks' risk-taking and thereby become self-reinforcing. In contrast, after a longer bust phase, the bubble may be less harmful because the shock fades out.

We do not include time fixed effects in the baseline regressions because these would absorb part of the variation that we are interested in. To clarify the argument, suppose we had only two countries in the sample that exhibit a bubble at the same time and banks experience the same increase in systemic risk. With time fixed effects, the coefficients of the bubble indicators would capture the change in systemic risk relative to the average of the two countries. Then, the coefficients of the bubble indicators would suggest no change in systemic risk during asset price bubbles (relative to the global average). In Section 3.6.1, we analyze the robustness of our results with respect to time and country-time fixed effects and find that most results continue to hold.

On the country level, we include a banking crisis dummy, real GDP growth to capture national business cycles, and inflation, which has been identified as a factor contributing to the occurrence of financial crises (Demirgüç-Kunt and Detragiache, 1998).[18] The 10-year government bond rates (in logs) account for the nexus between sovereigns and banks. Growth of investment to GDP is included to control for the use of credit for investment versus consumption (see Schularick and Taylor, 2012).

One concern in our empirical model could be reverse causality, leading to biased results regarding the effect of asset price bubbles on systemic risk. In a micro-level analysis, reverse causality is less of an issue than in analyses at macroeconomic level because systemic risk contributions at bank level are less likely to impact asset price bubbles than aggregate systemic risk. Nevertheless, it is plausible that banks themselves play a role in the creation of asset price bubbles. Cheap financing during a credit boom may lead to large real estate investments which may culminate in, or reinforce, a real estate bubble. Since we explicitly control for banks' loan growth, this would not bias our results. To further alleviate the concern of reserve causality, we also control for a number of other bank characteristics and, in some specifications, further lags of the explanatory variables.[19] These precautions make it less likely that our estimates suffer from reverse causality. In another robustness check, we estimate simple linear probability models and run Granger causality tests to check whether ΔCoVaR or MES predict asset price bubbles. We do not find any indication of reverse causality in these tests (see Tables 3.C.9 and 3.C.10). Nevertheless, we are conservative in the interpretation of our results and speak of an increase in systemic risk *during* rather than *due to* asset price bubbles throughout the paper. From a policy perspective, a two-way relationship could even strengthen the case for particular regulatory and supervisory attention because this could lead to a vicious loop, amplifying the initial effects.

Standard errors are clustered at bank and time level. The clustering at bank level accounts for autocorrelation, including that introduced by interpolation of the data. The clustering at time level allows error terms to be correlated across banks in all countries, which

[18] In Section 3.6.4, we account for business cycles more extensively, but find our results to be highly robust.
[19] Table 3.C.8 demonstrates that our results are robust to using different lag structures.

is important in light of several countries experiencing asset price bubbles at similar times. Since the precise timing of asset price booms and busts differs across countries, the bubble indicators show, however, variation in the cross-sectional dimension even for those countries that experience asset price bubbles in similar periods. The results are robust to alternative clustering of standard errors (see Table 3.C.11).

3.4 Results

3.4.1 Asset price bubbles and systemic risk in booms and busts

We start by illustrating the underlying conditional correlations without allowing for heterogeneous effects across banks. To this end, we regress ΔCoVaR on the bubble indicators, macroeconomic control variables, and bank fixed effects. We find that the coefficients of all four bubble indicators are positive and highly significant (Table 3.4, column 1). Overall, asset price bubbles are associated with a significant increase in systemic risk. The strongest relationship is found for real estate busts.

When looking at individual countries (results not reported), we find a significant positive association between asset price bubbles and systemic risk for twelve out of 17 countries in our sample. The relationship is insignificant in four countries and significantly negative only in a single country and only in the boom period.[20] Hence, the underlying correlation is pervasive in our sample and not driven by individual countries.

The signs of the coefficients of macroeconomic control variables are largely in line with expectations. Systemic risk is significantly elevated during banking crises, and it is negatively related to real GDP growth. Higher investment-to-GDP growth is negatively related to systemic risk, but the relationship is not statistically significant. Similarly, the coefficient of inflation is insignificant, but points in the expected positive direction. The 10-year government bond rate is negative (but later turns insignificant when bank controls are included).

[20] The negative correlation is found for asset price bubbles in Denmark. Insignificant correlations are estimated for Switzerland, Germany, Portugal and Sweden. These results are obtained without distinguishing between asset classes due to the low number of bubble episodes per country for each asset class.

Table 3.4: Systemic risk during bubble episodes across bank and bubble characteristics

Bubble estimates are based on the BSADF approach. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	ΔCoVaR			
Real estate boom	0.20***	0.15***	0.09**	0.11***
	(0.000)	(0.000)	(0.031)	(0.004)
Real estate bust	0.46***	0.27**	0.25**	0.27**
	(0.000)	(0.019)	(0.036)	(0.018)
Stock boom	0.30***	0.38***	0.34***	0.36***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.35***	0.37***	0.38***	0.38***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)		0.27***	0.26***	0.25***
		(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom		-0.01	-0.01	-0.01
		(0.533)	(0.490)	(0.492)
log(Bank size) · Real estate bust		0.14***	0.17***	0.16***
		(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom		0.05**	0.07***	0.06***
		(0.018)	(0.002)	(0.003)
log(Bank size) · Stock bust		0.11***	0.11***	0.11***
		(0.000)	(0.000)	(0.000)
Loan growth		-2.28***	-1.49**	-1.59**
		(0.001)	(0.020)	(0.014)
Loan growth · Real estate boom		2.51***	1.43**	1.58**
		(0.001)	(0.044)	(0.026)
Loan growth · Real estate bust		6.19***	4.47***	4.58***
		(0.000)	(0.003)	(0.002)
Loan growth · Stock boom		1.89**	0.86	1.03
		(0.011)	(0.202)	(0.140)
Loan growth · Stock bust		3.55***	2.81***	2.94***
		(0.001)	(0.001)	(0.001)
Leverage		0.00*	0.00*	0.00
		(0.061)	(0.097)	(0.107)
Leverage · Real estate boom		0.01**	0.01**	0.01**
		(0.021)	(0.028)	(0.020)
Leverage · Real estate bust		-0.01	-0.01	-0.01
		(0.254)	(0.123)	(0.206)
Leverage · Stock boom		-0.01***	-0.01***	-0.01***
		(0.001)	(0.002)	(0.001)
Leverage · Stock bust		-0.02***	-0.02***	-0.02***
		(0.000)	(0.000)	(0.000)
Maturity mismatch		-0.66***	-0.65***	-0.62***
		(0.000)	(0.000)	(0.000)
MM · Real estate boom		0.27***	0.21**	0.18*
		(0.004)	(0.024)	(0.051)
MM · Real estate bust		0.40*	0.33	0.41*
		(0.072)	(0.122)	(0.063)
MM · Stock boom		0.65***	0.38***	0.48***
		(0.000)	(0.000)	(0.000)
MM · Stock bust		0.40***	0.31**	0.43***
		(0.001)	(0.020)	(0.000)

(*table continued on next page*)

Table 3.4 - *continued*

	(1)	(2)	(3)	(4)
Dependent variable:		ΔCoVaR		
Real estate boom length			-0.01	
			(0.224)	
Real estate boom size				-0.00
				(0.937)
Real estate bust length			-0.14***	
			(0.000)	
Real estate bust size				-0.26***
				(0.009)
Stock boom length			0.16***	
			(0.000)	
Stock boom size				0.04***
				(0.000)
Stock bust length			-0.32***	
			(0.001)	
Stock bust size				-0.13
				(0.112)
Banking crisis	0.27***	0.23***	0.19***	0.22***
	(0.000)	(0.000)	(0.001)	(0.000)
GDP growth	-4.22**	-2.50	-3.90**	-3.85**
	(0.019)	(0.132)	(0.020)	(0.026)
log(Interest rate)	-0.22***	-0.01	-0.04	-0.03
	(0.000)	(0.780)	(0.350)	(0.491)
Inflation	4.81	5.97	7.19*	7.08*
	(0.237)	(0.139)	(0.084)	(0.094)
Investment-to-GDP growth	-0.40	-0.72**	-0.52	-0.56*
	(0.198)	(0.036)	(0.111)	(0.080)
Bank FE	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	165,149	165,149
Adj. R^2	0.819	0.827	0.831	0.830
Adj. R^2 within	0.082	0.123	0.141	0.135

3.4.2 The role of bank and bubble characteristics

The results presented above provide first evidence of higher systemic risk during bubble episodes. We now ask what is the role of bank and bubble characteristics for the relationship between asset price bubbles and systemic risk. Column 2 of Table 3.4 reports regressions including the bank-level variables and their interactions with the bubble indicators. In columns 3 and 4, we add the two bubble characteristics, leading to our baseline regression from Equation (3.3).

The inclusion of interaction terms leaves the coefficients of the bubble indicators qualitatively unchanged. However, it alters their interpretation as they now refer to a bank with median bank (and bubble) characteristics. Hence, the systemic risk contribution of a bank with median balance sheet characteristics increases significantly during all four bubble phases (column 2). This finding also holds for bubble phases of average size or length (columns 3 and 4). The coefficients of bank characteristics during non-bubble times are in line with the previous literature. As in Adrian and Brunnermeier (2016), the systemic risk contributions increase in the size of an institution as well as in leverage, but decrease in an institution's maturity mismatch.[21] Loan growth is highly significant with a negative sign, implying that higher loan growth goes along with lower systemic risk in normal times. This finding proves to be very robust throughout the analysis, which suggests healthy loan growth outside of bubble periods.

Interestingly, the relationship between bank characteristics and systemic risk contributions changes markedly during bubble episodes (see the results in column 2). For example, bank size is associated with larger increases in systemic risk contributions during real estate and stock market busts and, to a lesser extent, also during stock market booms. Hence, apart from real estate booms, large banks' contributions to systemic risk appear to increase more strongly than those of small banks during asset price bubbles, as would be expected due to their greater power to spread risks throughout the financial system. The negative but insignificant coefficient of the interaction between bank size and real estate booms may be related to a more active role of small banks in financing the bubble. Loan growth is less benign in bubble episodes than in normal times. While the relationship between loan growth and systemic risk is negative in normal times, this relationship vanishes during bubble episodes. During real estate busts, systemic risk contributions even increase in lending growth, as the sum of the coefficients of loan growth and its interaction with the bust indicators becomes positive and statistically significant (test not reported). This underlines the dangers of high lending growth for financial stability during bubble episodes when rising prices induce unhealthy lending, the risks of which materialize in the bust. Similarly, the regressions show a significantly less negative relationship between maturity mismatch and systemic risk during all types of bubble episodes. Hence, higher maturity mismatch appears more problematic during bubble episodes. The results on leverage are mixed as its interaction has a significantly positive coefficient only during real estate booms, while it is not statistically significant during real estate busts and significantly negative during stock market bubbles. Overall, these regressions strongly support the relevance of bank characteristics for the relationship between asset price bubbles and systemic risk.

[21] Adrian and Brunnermeier (2016) define the maturity mismatch inversely to our definition such that the different sign of the corresponding coefficient in our paper is in line with the respective finding in that paper.

When adding bubble length and size to our analysis (columns 3 and 4), these results regarding bank characteristics during and outside of bubble episodes remain almost identical. Since *length* and *size* are highly correlated, it is impossible to distinguish their effects empirically. Therefore, they enter the regressions separately. We find that during stock market booms the coefficients of *length* and *size* are positive and significant. This is plausible as longer booms are likely to lead to a larger build-up of imbalances in the financial system and larger booms have the potential for a more pronounced bust after the burst. The coefficients of size and length are insignificant during real estate booms. The increase in systemic risk during these episodes appears to depend more on bank than on bubble characteristics. During real estate and stock market busts, the coefficients of the two bubble characteristics are negative and, with the exception of bubble size during stock market busts, statistically significant. This could be explained by a fading out of the initial shock of the burst and policy interventions alleviating the consequences of the burst at later stages of the bust.

3.4.3 Economic significance and aggregate effects

We now analyze the economic significance of the observed increase in systemic risk during bubble episodes and discuss the quantitative importance of bank and bubble characteristics. During a stock market boom or bust with median bubble characteristics, ΔCoVaR increases by around 0.37 percentage points relative to normal times for a bank of median size, loan growth, leverage, and maturity mismatch (average of columns 3 and 4 in Table 3.4). This corresponds to 22 percent (=0.37/1.68) of the median level of ΔCoVaR. The corresponding increases associated with the boom and bust of real estate bubbles amount to 6 and 15 percent, respectively.

From a financial stability perspective, we are more concerned about extreme events, i. e., about a bank like Lehman Brothers during the US subprime housing bubble rather than some average bank during a median bubble.[22] To account for this heterogeneity, we quantify the dependence of the systemic risk increase on bank and bubble characteristics. The

[22]The Lehman collapse is not the only case where the failure of prominent financial institutions triggered a systemic crisis. Well-known historical examples are the collapse of the banking house de Neufville Brothers in the crisis of 1763 (Schnabel and Shin, 2004), Overend, Gurney & Company in the Panic of 1866 (Collins, 1992), or Österreichische Creditanstalt and Danatbank in the crises of 1931 (Schnabel, 2004). More formally, we run regressions analyzing how the median and the spread between the maximum and the median of ΔCoVaR affect the probability of banking or financial crises in a country. The spread has predictive power for both types of crises beyond the median (see Table 3.C.12), supporting the importance of one or a few particularly risky banks for financial stability.

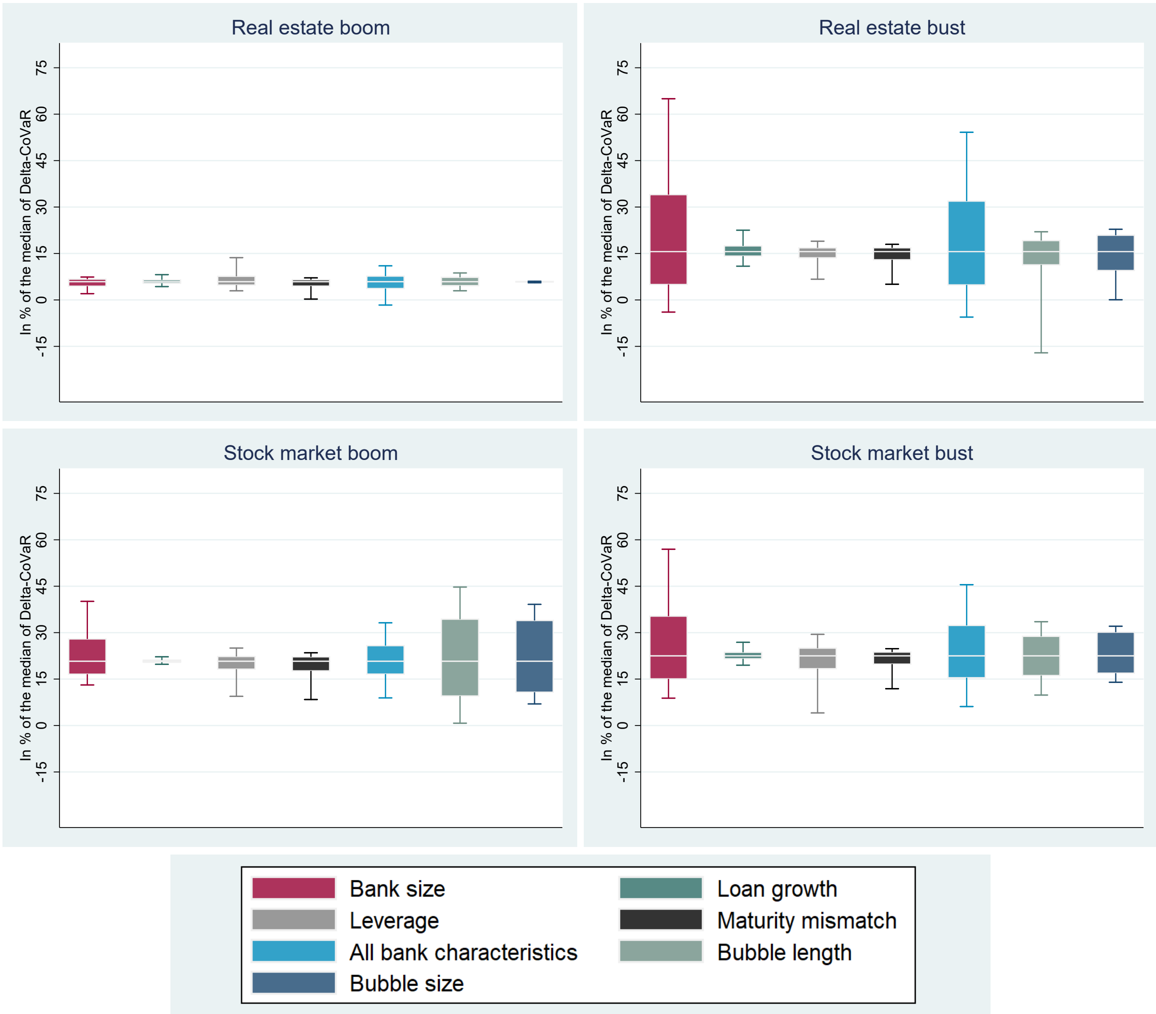
boxplots in Figure 3.5 illustrate the distribution of the increase in systemic risk relative to the median of ΔCoVaR. Specifically, it depicts the median increase (white horizontal line in each box), the 75^{th} and 25^{th} percentile (upper and lower end of each box), and the 95^{th} and 5^{th} percentile of the increase in systemic risk (whiskers) in dependence of bank and bubble characteristics. There is no reason to expect the largest bank to also exhibit the largest loan growth, leverage, and maturity mismatch. Correspondingly, the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics. Moreover, as bubble length and size are highly correlated, their effects do not add up. Since we cannot simultaneously include bubble length and size due to the high correlation of both variables, the figure is based on the average of the estimated coefficients in our two baseline regressions (Table 3.4, columns 3 and 4).

The boxplots yield interesting insights. With the exception of stock market booms, the increase in systemic risk depends more on bank than on bubble characteristics. This corresponds well to the narrative of the rather small shock from the US subprime housing bubble that was amplified due to imbalances in the financial sector. Comparing boom and bust phases, the bust phases exhibit a larger median increase in systemic risk, but also a larger range of the increase. Hence, an emerging asset price bubble goes along with increased financial fragility, yet it is only during the bust phase that the full risk associated with the bubble materializes. During real estate busts, the 95^{th} percentile of the increase in systemic risk in dependence of bank characteristics amounts to 55 percent of the median of ΔCoVaR, the 99^{th} percentile to almost 70 percent. For stock market busts, the corresponding increases are 46 and 56 percent, respectively.

The most important factor driving the heterogeneity of effects during bubble episodes is bank size, especially during bust phases. This is plausible as a large bank under distress due to the burst of an asset price bubble has a much higher potential to transmit this distress to the rest of the financial system. The systemic risk contribution of a bank with bank size at the 95^{th} percentile of the size distribution increases by approximately 70 percent of the median of ΔCoVaR during real estate busts and by almost 60 percent during stock market busts. To put these estimates further into perspective, we predict ΔCoVaR for Lehman Brothers once with the actual values of all variables and once assuming no bubble had been present. According to our estimation, at the time of the burst of the US subprime housing bubble, the systemic risk posed by Lehman Brothers would have been 40 percent lower if the bubble had not existed.

Figure 3.5: Systemic risk during bubble episodes across bank and bubble characteristics

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔCoVaR. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. All results rely on the average of the estimated coefficients in our two baseline regressions (Table 3.4, columns (3) and (4)). The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.



These results do not support the view that real estate bubbles are generally more harmful than their stock market counterparts. Instead, the ordering depends on bank characteristics. For example, stock market busts appear to be more harmful than real estate busts at median bank characteristics, while the latter are more harmful at sufficiently unfavorable bank characteristics. Moreover, our results support the view that developments within the financial sector are more relevant than a bubble's asset class, as also argued by Brunnermeier and Schnabel (2016).

An interesting question is how the risk increase at bank level is reflected in changes in aggregate systemic risk. Since the range of the increase is mostly positive (Figure 3.5), systemic risk is likely to increase also in the aggregate. To test this conjecture more formally, we aggregate ΔCoVaR at country level by calculating averages weighted by bank size and regress it on the bubble indicators, bubble characteristics, and country fixed effects. The results in Table 3.5 (columns 1 and 2) show a significant increase in aggregate systemic risk during real estate and stock market bubbles. The increase is most pronounced during real estate bubbles, and especially real estate busts where it amounts to about 0.8 standard deviations of the aggregate ΔCoVaR. When controlling for median bank characteristics and their interactions with the bubble indicators (columns 3 and 4) or adding macro controls (columns 5 and 6), the coefficients decrease but remain significant in economic and statistical terms. Overall, these results strongly support the view that the increase in systemic risk at bank level translates into a significant increase in aggregate systemic risk.[23]

3.5 Results for alternative measures

Our baseline results are based on regressions using one identification procedure for asset price bubbles and one specific measure of systemic risk. While the measures we rely on are widely used, others constitute reasonable alternatives. Therefore, we repeat our regressions using alternative measures of asset price bubbles and systemic risk.

3.5.1 Results using alternative bubble measures

We first repeat our main analyses using the alternative bubble measures, namely the BSADF approach to price-to-rent and price-to-dividend data, or the trend-deviation approach (see Section 3.3.2). Table 3.6 restates our two baseline regressions alongside estimates obtained from an identical specification, but using the alternative bubble measures.

[23] The value at risk of two portfolios is generally not additive, as the correlation between portfolios has to be taken into account. This also applies to ΔCoVaR. Therefore, we refrain from further analyses at aggregate level.

Table 3.5: Regressions at country level

ΔCoVaR is aggregated at country level by calculating bank-size weighted averages. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Bank characteristics (size, leverage, loan growth, maturity mismatch) are median values across banks within a country per point in time. "Bubble interactions" refers to the interaction of these bank characteristics with the bubble indicators. Standard errors are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ΔCoVaR					
Real estate boom	0.73***	0.52***	0.74***	0.70***	0.77***	0.82***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real estate bust	1.22***	1.32***	1.06***	1.11***	0.80***	0.90***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock boom	0.39***	0.18**	0.56***	0.38***	0.66***	0.49***
	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.50***	0.49***	0.58***	0.54***	0.62***	0.61***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Bubble length	Yes	No	Yes	No	Yes	No
Bubble size	No	Yes	No	Yes	No	Yes
Median bank char.	No	No	Yes	Yes	Yes	Yes
Bubble interactions	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Effects in standard deviations of the dependent variable						
Real estate boom	0.46	0.33	0.46	0.44	0.48	0.51
Real estate bust	0.77	0.82	0.66	0.69	0.5	0.56
Stock boom	0.24	0.11	0.35	0.24	0.41	0.31
Stock bust	0.31	0.31	0.36	0.34	0.39	0.38
No. of obs.	5,228	5,228	5,208	5,208	5,208	5,208
Adj. R^2	0.384	0.382	0.498	0.493	0.537	0.529
Adj. R^2 within	0.131	0.129	0.292	0.285	0.348	0.335

Compared to the baseline results (columns 1 and 2), the regressions using bubbles identified through the BSADF test applied to normalized price data (columns 3 and 4) confirm most of our previous findings, with slightly lower significance levels. Again, all bubble episodes are associated with increased systemic risk at median bank and bubble characteristics. Moreover, systemic risk contributions increase in bank size, decrease in maturity mismatch, and do not significantly differ in leverage during normal times. The coefficients of loan growth remain negative but turn insignificant. During bubble episodes, we once more see that the increase in systemic risk during real estate busts and stock market booms and busts is more pronounced for larger banks. As in the baseline regressions, it is less pronounced during real estate booms, but the coefficient now turns significant. The relationship between loan growth and systemic risk during bubble episodes remains positive but becomes less significant during real estate bubbles and more significant during stock market booms. In economic terms, however, the relationship remains small (see Figure 3.C.3). The results on leverage remain mixed. For maturity mismatch, there is no significantly different relationship during real estate bubbles anymore, while results on stock market bubbles are unchanged.

The results on bubble characteristics are again similar. Some bubble characteristics lose significance, suggesting a higher relevance of bank characteristics. The coefficient on the size of real estate busts changes its sign, a finding that only appears in this particular specification. As before, bust phases of the bubble exhibit a higher level and a higher range of the systemic risk increase compared to the boom phases. Bank size remains the most relevant driver of the increase in systemic risk contributions (see Figure 3.C.3).

Table 3.6: The role of bank and bubble characteristics: alternative bubble measures

Columns 1 and 2 restate our baseline regressions from Table 3.4, columns 6 and 7. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Bubble estimation approach:	BSADF		BSADF normalized		Trend deviations	
Real estate boom	0.09**	0.11***	0.08**	0.08**	0.01	0.01
	(0.031)	(0.004)	(0.027)	(0.037)	(0.747)	(0.756)
Real estate bust	0.25**	0.27**	0.20***	0.14**	0.22*	0.22*
	(0.036)	(0.018)	(0.001)	(0.010)	(0.056)	(0.054)
Stock boom	0.34***	0.36***	0.45***	0.46***	0.54***	0.54***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.50***	0.51***	0.41***	0.42***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.26***	0.26***	0.26***	0.26***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.04**	-0.04**	-0.07***	-0.07***
	(0.490)	(0.492)	(0.011)	(0.019)	(0.000)	(0.000)
log(Bank size) · Real estate bust	0.17***	0.16***	0.09***	0.08***	0.17***	0.17***
	(0.000)	(0.000)	(0.001)	(0.005)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.09***	0.09***	0.08***	0.08***
	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock bust	0.11***	0.11***	0.16***	0.16***	0.10***	0.10***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**	-0.52	-0.80	-0.76	-0.68
	(0.020)	(0.014)	(0.407)	(0.204)	(0.184)	(0.247)
Loan growth · Real estate boom	1.43**	1.58**	0.44	0.76	0.63	0.50
	(0.044)	(0.026)	(0.578)	(0.331)	(0.372)	(0.477)
Loan growth · Real estate bust	4.47***	4.58***	1.22	2.36**	2.01*	1.86
	(0.003)	(0.002)	(0.275)	(0.034)	(0.089)	(0.112)
Loan growth · Stock boom	0.86	1.03	1.78**	2.25**	1.52*	1.56*
	(0.202)	(0.140)	(0.041)	(0.016)	(0.087)	(0.077)
Loan growth · Stock bust	2.81***	2.94***	3.39***	3.70***	2.55***	2.60***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.005)	(0.004)

(*table continued on next page*)

Table 3.6 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ΔCoVaR					
Bubble estimation approach:	BSADF		BSADF normalized		Trend deviations	
Leverage	0.00*	0.00	0.00	0.00	0.00**	0.00**
	(0.097)	(0.107)	(0.481)	(0.459)	(0.030)	(0.025)
Leverage · Real estate boom	0.01**	0.01**	0.01***	0.01***	0.01***	0.01***
	(0.028)	(0.020)	(0.001)	(0.001)	(0.001)	(0.002)
Leverage · Real estate bust	-0.01	-0.01	0.01	0.01	-0.01**	-0.01**
	(0.123)	(0.206)	(0.279)	(0.254)	(0.025)	(0.024)
Leverage · Stock boom	-0.01***	-0.01***	-0.01**	-0.01***	-0.02***	-0.02***
	(0.002)	(0.001)	(0.012)	(0.010)	(0.000)	(0.000)
Leverage · Stock bust	-0.02***	-0.02***	-0.03***	-0.03***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch	-0.65***	-0.62***	-0.58***	-0.58***	-0.59***	-0.59***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.12	0.11	0.05	0.02
	(0.024)	(0.051)	(0.213)	(0.225)	(0.673)	(0.856)
MM · Real estate bust	0.33	0.41*	-0.02	-0.02	0.21	0.25
	(0.122)	(0.063)	(0.882)	(0.911)	(0.313)	(0.234)
MM · Stock boom	0.38***	0.48***	0.31***	0.36***	0.86***	0.85***
	(0.000)	(0.000)	(0.007)	(0.002)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.47***	0.47***	0.46***	0.41***
	(0.020)	(0.000)	(0.010)	(0.005)	(0.002)	(0.008)
Real estate boom length	-0.01		-0.01		-0.01	
	(0.224)		(0.103)		(0.476)	
Real estate boom size		-0.00		-0.01		-0.01
		(0.937)		(0.259)		(0.677)
Real estate bust length	-0.14***		0.01		-0.09*	
	(0.000)		(0.768)		(0.088)	
Real estate bust size		-0.26***		0.43***		-0.14
		(0.009)		(0.002)		(0.283)
Stock boom length	0.16***		0.16***		0.14***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.04***		0.06***		0.04**
		(0.000)		(0.000)		(0.013)
Stock bust length	-0.32***		-0.28		-0.46***	
	(0.001)		(0.263)		(0.000)	
Stock bust size		-0.13		0.00		-0.14**
		(0.112)		(0.975)		(0.017)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	165,134	165,134	165,149	165,149
Adj. R^2	0.831	0.830	0.829	0.829	0.832	0.832
Adj. R^2 within	0.141	0.135	0.131	0.132	0.149	0.145

The results based on bubbles estimated with the trend-deviation approach are very similar to those using the normalized price series, with one exception. The increase in systemic risk during real estate booms at median bank and bubble characteristics turns insignificant. Nevertheless, real estate booms cannot be discarded on the basis of this result. As argued before, extreme cases are more relevant from a financial stability perspective than the median bank. In fact, for unfavorable bank characteristics, ΔCoVaR again increases significantly also in real estate booms. During real estate busts, the increase in ΔCoVaR is already statistically significant for a bank with median characteristics, but again it is larger for unfavorable bank characteristics. In that case, it amounts to more than 60 percent of the median of ΔCoVaR (see Figure 3.C.4). Hence, despite some quantitative differences, the regressions with the alternative bubble measures support the finding that systemic risk increases during asset price bubbles, especially for unfavorable bank characteristics. As before, bank size stands out, while the results on bubble characteristics are slightly weaker than before, at least for real estate bubbles.

3.5.2 Results using MES as an alternative systemic risk measure

To assess whether the results depend on the choice of systemic risk measure, we repeat our baseline regressions using MES instead of ΔCoVaR. In the interpretation, one has to keep in mind the conceptual differences between the two measures. A higher MES signals a larger systemic risk *exposure* of a bank. In contrast, a higher ΔCoVaR stands for a larger systemic risk *contribution* of a bank. Based on the similar evolution of ΔCoVaR and MES in the aggregate (see Figure 3.4), we expect MES to also increase during bubble episodes. In contrast, due to the conceptual differences, there is no reason to expect the same relationships with bank characteristics. In fact, ΔCoVaR has been shown to react more to the size of banks, while other measures are driven more by leverage (see, e. g., Benoit et al., 2013).

Table 3.7 shows the results from re-running our baseline regressions with MES instead of ΔCoVaR as dependent variable. As before, systemic risk increases during stock market bubbles at median bank and bubble characteristics. For real estate bubbles, the increase in systemic risk is significant only for the bust phase and only when lagged data series are used, but then with a very large coefficient. The coefficients on bank characteristics in normal times are also similar to before. As ΔCoVaR, MES increases in bank size and decreases in loan growth and maturity mismatch outside of bubble episodes. Leverage now has a significantly negative effect in columns 1 and 2 suggesting a higher systemic risk exposure for better capitalized banks. This may reflect the fact that better capitalized banks can afford to be riskier and therefore take higher asset risk.

Again, the relationship between asset price bubbles and systemic risk depends on bank characteristics. Small banks' systemic risk exposure rises relative to that of large banks during real estate booms. This is plausible as large banks are often less active in mortgage lending than smaller banks. The effect tends to reverse in the bust phase when large banks' exposure increases more strongly in some specifications (see columns 3 and 4). During stock market bubbles, large banks' exposure tends to rise more strongly in booms and busts, which is consistent with a higher share of market-based activities. Notwithstanding the described *changes* in systemic risk, larger banks have a larger *level* of systemic risk exposure at all times, as the sum of the coefficients of bank size and its interaction is positive.

The relationship between loan growth and MES during asset price bubbles is not statistically different from normal times. Hence, loan growth during asset price bubbles appears to increase banks' potential to contribute risk to the financial system but not their exposure to systemic risk. The results on leverage point more strongly in a risk-increasing direction. Higher leverage is associated with a higher risk exposure especially during real estate booms, suggesting that poorly capitalized banks become highly vulnerable in such periods. Somewhat surprisingly, the sign reverses during stock market busts. The findings regarding the interactions between maturity mismatch and the bubble indicators show another noteworthy difference. The corresponding interactions with real estate booms and busts are still significantly positive or insignificant. The interactions with stock market booms and busts, however, are now negative and significant. This could reflect the fact that banks with a stronger focus on the traditional banking business involving higher maturity transformation are less susceptible to market risk especially during stock market bubbles. If the overall effect of maturity mismatch during bubble episodes is considered (i. e., the sum of the single and the interaction term), the relationship between the maturity mismatch and systemic risk is negative or insignificant for both MES and ΔCoVaR.

Looking at bubble characteristics, the results are very similar to before. During a stock market boom, MES increases in bubble size and length, pointing towards the potential for a more pronounced bust. MES decreases in bubble size and length during the bust phase of stock market and real estate bubbles. Hence, we again see a fading impact of the burst, potentially due to policy measures alleviating financial sector distress.

Considering economic significance, the results are very similar (see Figure 3.C.5). As before, the boxplots corresponding to the regression results show a larger dependence of the increase in systemic risk on bank than on bubble characteristics. For MES, this ordering also applies during stock market booms. Bust phases exhibit larger increases in systemic risk. And bank size is a dominant factor driving the heterogeneity across banks. Hence, while the specific interpretation of the interaction terms differs due to the different interpretations of the two measures, the main finding regarding the important role of bank characteristics is highly robust.

Table 3.7: The role of bank and bubble characteristics: alternative systemic risk measure

Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Columns 3 and 4 report regressions with all explanatory variables lagged by an additional 6 months. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Real estate boom	0.04	0.06	0.05	0.05
	(0.421)	(0.249)	(0.353)	(0.352)
Real estate bust	0.01	0.03	0.47***	0.53***
	(0.910)	(0.757)	(0.000)	(0.000)
Stock boom	0.10*	0.11*	0.16**	0.16**
	(0.078)	(0.062)	(0.017)	(0.021)
Stock bust	0.25***	0.25***	0.21***	0.21***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.66***	0.66***	0.76***	0.74***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.20***	-0.20***	-0.17***	-0.17***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate bust	-0.01	-0.04	0.14**	0.11*
	(0.814)	(0.458)	(0.011)	(0.072)
log(Bank size) · Stock boom	-0.00	-0.01	0.06*	0.06*
	(0.923)	(0.820)	(0.066)	(0.054)
log(Bank size) · Stock bust	0.09***	0.09***	0.12***	0.12***
	(0.004)	(0.004)	(0.000)	(0.000)
Loan growth	-6.08***	-6.07***	-3.10*	-3.15*
	(0.000)	(0.000)	(0.078)	(0.071)
Loan growth · Real estate boom	2.02	2.09	0.35	0.37
	(0.255)	(0.237)	(0.848)	(0.842)
Loan growth · Real estate bust	2.52	2.98	2.99	4.38
	(0.418)	(0.360)	(0.370)	(0.210)
Loan growth · Stock boom	0.76	0.81	1.36	1.31
	(0.671)	(0.656)	(0.461)	(0.471)
Loan growth · Stock bust	3.19	3.08	2.15	2.17
	(0.208)	(0.229)	(0.351)	(0.346)

(*table continued on next page*)

Table 3.7 - *continued*

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Leverage	-0.01**	-0.01**	-0.00	-0.00
	(0.048)	(0.045)	(0.784)	(0.712)
Leverage · Real estate boom	0.03***	0.03***	0.02***	0.02***
	(0.000)	(0.000)	(0.005)	(0.002)
Leverage · Real estate bust	0.02**	0.03***	-0.01	-0.00
	(0.015)	(0.006)	(0.467)	(0.754)
Leverage · Stock boom	0.01	0.01	0.00	0.00
	(0.136)	(0.231)	(0.819)	(0.914)
Leverage · Stock bust	-0.03***	-0.02***	-0.02***	-0.02**
	(0.000)	(0.001)	(0.009)	(0.017)
Maturity mismatch	-0.86***	-0.85***	-1.10***	-1.05***
	(0.005)	(0.006)	(0.000)	(0.001)
MM · Real estate boom	0.06	-0.01	0.21	0.08
	(0.789)	(0.972)	(0.365)	(0.723)
MM · Real estate bust	0.32	0.44	1.19***	1.30***
	(0.368)	(0.219)	(0.003)	(0.001)
MM · Stock boom	-1.14***	-1.05***	-1.22***	-1.23***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	-0.73***	-0.60**	-0.84***	-0.73***
	(0.007)	(0.022)	(0.001)	(0.003)
	(1)	(2)	(3)	(4)
Real estate boom length	-0.02		-0.02	
	(0.131)		(0.110)	
Real estate boom size		-0.01		0.00
		(0.328)		(0.873)
Real estate bust length	-0.24***		-0.33***	
	(0.000)		(0.000)	
Real estate bust size		-0.33***		-0.22**
		(0.000)		(0.040)
Stock boom length	0.23***		0.13***	
	(0.000)		(0.000)	
Stock boom size		0.06***		0.04***
		(0.000)		(0.000)
Stock bust length	-0.41***		-0.30***	
	(0.000)		(0.000)	
Stock bust size		-0.22***		-0.15***
		(0.000)		(0.006)
Bank FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
No. of obs.	162,092	162,092	160,980	160,980
Adj. R^2	0.472	0.470	0.454	0.452
Adj. R^2 within	0.218	0.216	0.194	0.191

3.6 Further robustness checks

In this section, we assess the robustness of our baseline results in several directions. First, we account for ΔCoVaR's variation coming from developments at macro level by considering additional control variables, additional fixed effects, and an alternative estimation strategy for ΔCoVaR. Second, we analyze the sensitivity of results with respect to banks' size by considering sample splits and, alternatively, by weighting observations by bank size. Third, we evaluate whether the results are driven by particular episodes such as the global financial crisis, which stands out due to its spike in systemic risk.

3.6.1 Controlling for additional variation at macro level

We first check whether the results in the regressions using ΔCoVaR depend on specific properties of this measure, in particular the inclusion of macroeconomic variables in the estimation. While the cross-sectional variation in ΔCoVaR is driven by bank-specific factors, its time series variation is driven by these macroeconomic variables, which vary over time at the financial system level (see Appendix 3.B). None of these variables is directly related to real estate price dynamics, but the variables include stock market returns and volatility. This may not be a concern during stock market booms, as ΔCoVaR relies on conditional correlations in the left tail of the return distributions of the financial system and individual banks. It may, however, raise concerns regarding our estimates on stock market busts. In this robustness check, we therefore want to exclude that the results are driven by a mechanical correlation due to stock market returns and volatilities being included in both the systemic risk estimation and the bubble estimation.

In columns 1 and 2 of Table 3.8, we add the stock market return and volatility as additional controls to absorb the corresponding variation (coefficients of controls not displayed). The coefficients of the real estate bubble indicators prove to be fully robust. However, the coefficient of the stock market boom indicator becomes smaller, and the one on stock market busts even insignificant. Hence, it cannot be ruled out that the estimated increase in systemic risk during stock market bubbles is partly driven by the involvement of the stock market return and volatility during the estimation of the systemic risk measure. At the same time, the coefficients of all bank characteristics and their interactions with the bubble indicators are robust. The coefficients of the variables capturing bubble characteristics are also similar but become smaller in absolute terms. This further supports the larger relevance of bank characteristics compared to bubble characteristics for the increase in systemic risk. As before, real estate busts go along with a larger increase in systemic risk than stock market busts for unfavorable bank characteristics. In this robustness check, this ordering also applies for the bust phases at median bank characteristics.

We also run regressions with time fixed effects to account for global factors (columns 3 and 4). As expected, the increase in systemic risk during bust episodes turns insignificant at the median level of bank and bubble characteristics, as the bust phases are generally short and often take place simultaneously to boom or bust phases in other countries (see Figure 3.3) such that the remaining variation is limited. In contrast, the bank-level variables and, hence, their interactions with the bubble indicators, as well as the bubble characteristics still show substantial variation when including time fixed effects. In line with this observation, our main results, particularly the significant increase in systemic risk for banks with unfavorable characteristics, are confirmed. This also applies when we consider the full bubble episodes without distinguishing between boom and bust phases (see Table 3.C.3, column 2).

Table 3.8: Controlling for additional variation at the macro level

Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. The additional macroeconomic variables in columns 1 and 2 are the stock price returns and volatilities used during the estimation of ΔCoVaR (see Appendix 3.B). The estimation strategy of the rolling ΔCoVaR is described in Section 3.6.1. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:			ΔCoVaR			Rolling ΔCoVaR	
Real estate boom	0.13***	0.14***	0.21***	0.22***		0.24***	0.24***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Real estate bust	0.28***	0.29***	-0.07	-0.08		0.38***	0.36***
	(0.000)	(0.000)	(0.409)	(0.361)		(0.000)	(0.000)
Stock boom	0.18***	0.18***	0.27***	0.24***		0.26***	0.28***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Stock bust	0.08	0.07	0.06	0.01		0.37***	0.37***
	(0.137)	(0.181)	(0.352)	(0.860)		(0.000)	(0.000)
log(Bank size)	0.10***	0.09***	0.04	0.04	0.01	0.26***	0.25***
	(0.000)	(0.001)	(0.203)	(0.199)	(0.812)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.02	-0.02	-0.03	-0.03	-0.04	-0.15***	-0.15***
	(0.373)	(0.336)	(0.130)	(0.130)	(0.108)	(0.000)	(0.000)
log(Bank size) · Real estate bust	0.16***	0.16***	0.19***	0.18***	0.20***	0.13***	0.09*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.056)
log(Bank size) · Stock boom	0.07***	0.07***	0.06***	0.06***	0.07***	0.06**	0.05**
	(0.001)	(0.001)	(0.003)	(0.004)	(0.002)	(0.049)	(0.047)
log(Bank size) · Stock bust	0.11***	0.12***	0.12***	0.12***	0.14***	0.17***	0.17***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.77***	-1.79***	-2.17***	-2.19***	-2.02***	-4.79***	-4.95***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Loan growth · Real estate boom	2.25***	2.22***	2.04***	2.05***	2.23***	1.60	1.84
	(0.001)	(0.001)	(0.004)	(0.004)	(0.001)	(0.234)	(0.172)
Loan growth · Real estate bust	4.24***	4.36***	4.02***	4.23***	3.18**	3.78	5.32
	(0.003)	(0.002)	(0.005)	(0.003)	(0.012)	(0.221)	(0.104)
Loan growth · Stock boom	0.90	0.93	0.98	1.09*	0.70	3.41**	3.51**
	(0.142)	(0.139)	(0.103)	(0.074)	(0.193)	(0.017)	(0.013)
Loan growth · Stock bust	1.38*	1.24*	1.74**	1.68**	1.15*	3.68	3.49
	(0.068)	(0.100)	(0.018)	(0.024)	(0.075)	(0.102)	(0.136)

(*table continued on next page*)

Table 3.8 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:			ΔCoVaR			Rolling ΔCoVaR	
Leverage	0.00**	0.00**	0.00**	0.00**	0.00**	0.01***	0.01***
	(0.031)	(0.030)	(0.014)	(0.012)	(0.044)	(0.000)	(0.000)
Leverage · Real estate boom	0.01**	0.01**	0.01**	0.01**	0.01***	0.01*	0.01*
	(0.011)	(0.010)	(0.021)	(0.026)	(0.000)	(0.086)	(0.056)
Leverage · Real estate bust	-0.01**	-0.01*	-0.01*	-0.01	-0.01***	0.01	0.02
	(0.040)	(0.062)	(0.078)	(0.112)	(0.005)	(0.495)	(0.400)
Leverage · Stock boom	-0.01***	-0.01***	-0.02***	-0.02***	-0.01***	0.00	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.879)	(0.907)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)
Maturity mismatch	-0.47***	-0.46***	-0.42***	-0.43***	-0.33***	-1.04***	-1.02***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)	(0.000)	(0.000)
MM · Real estate boom	0.20**	0.20***	0.20**	0.21**	0.18**	0.40**	0.29*
	(0.014)	(0.010)	(0.021)	(0.013)	(0.025)	(0.025)	(0.089)
MM · Real estate bust	0.42**	0.46**	0.09	0.12	-0.13	1.14***	1.24***
	(0.024)	(0.016)	(0.617)	(0.490)	(0.455)	(0.000)	(0.000)
MM · Stock boom	0.46***	0.48***	0.54***	0.58***	0.03	0.19	0.24
	(0.000)	(0.000)	(0.000)	(0.000)	(0.735)	(0.225)	(0.136)
MM · Stock bust	0.21**	0.27***	0.40***	0.43***	-0.02	0.19	0.30
	(0.023)	(0.005)	(0.000)	(0.000)	(0.790)	(0.364)	(0.147)
Real estate boom length	0.01*		0.01*			-0.02***	
	(0.076)		(0.073)			(0.007)	
Real estate boom size		0.02***		0.01*			-0.01
		(0.006)		(0.063)			(0.183)
Real estate bust length	-0.10***		-0.09***			-0.25***	
	(0.001)		(0.001)			(0.001)	
Real estate bust size		-0.15**		-0.10**			-0.10
		(0.018)		(0.026)			(0.359)
Stock boom length	0.05		0.07***			0.15***	
	(0.141)		(0.004)			(0.000)	
Stock boom size		0.01		0.01			0.04***
		(0.258)		(0.165)			(0.000)
Stock bust length	-0.16***		-0.06			-0.24**	
	(0.006)		(0.271)			(0.016)	
Stock bust size		-0.10***		-0.09**			-0.16***
		(0.001)		(0.045)			(0.000)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CoVaR controls	Yes	Yes	No	No	No	No	No
Global time FE	No	No	Yes	Yes	No	No	No
Country-time FE	No	No	No	No	Yes	No	No
No. of obs.	165,149	165,149	165,149	165,149	164,934	162,776	162,776
Adj. R^2	0.865	0.865	0.878	0.878	0.891	0.674	0.672
Adj. R^2 within	0.313	0.313	0.063	0.061	0.044	0.161	0.156

When we add country-time fixed effects to our baseline regression (column 5 of Table 3.8), the bubble indicators, bubble characteristics, and macroeconomic control variables drop out as they vary only at country-time level. We can still assess the robustness of our results regarding the bank-level variables as well as their interactions with the bubble indicators. The statistical significance of the estimated coefficients is reduced due to the reduction in the degrees of freedom. At the same time, the basic results are again maintained remarkably well, which provides strong support for our previous findings.

We perform an additional robustness check to address ΔCoVaR's dependence on the financial system variables by modifying ΔCoVaR's estimation procedure. So far, ΔCoVaR relied on estimates of financial institutions' VaR (see Equation (3.10)). This estimated VaR introduces ΔCoVaR's dependence on financial system variables. As an alternative, we now calculate financial institutions' VaR directly from their past equity returns using one-year rolling windows. The windows are overlapping, as they move forward on a monthly basis. All other estimation details remain unchanged. The rolling ΔCoVaR can be expressed as

$$\Delta CoVaR^{i}_{q,t} = \hat{\beta}^{system|i}_{q}(VaR^{i}_{q,t} - VaR^{i}_{50,t}) \;, \tag{3.4}$$

where we drop the hats of the VaR as it is now calculated as opposed to estimated. The time variation in both the calculated VaR and the rolling ΔCoVaR is independent of the financial system variables. These variables are now exclusively used to control for general risk factors when estimating the dependence between bank returns and financial system returns (see Equation (3.11)). While the mean and the median of this rolling version of ΔCoVaR are slightly lower (1.59 and 1.23 vs. 1.96 and 1.68), the standard deviation is slightly higher (1.77 vs. 1.65). The evolution of the average rolling ΔCoVaR in all four financial systems is similar to its original counterpart. As before, there is a pronounced peak at the time of the global financial crisis. The euro area crisis and the Japanese banking crisis at the beginning of the 1990s show spikes, while the dotcom bubble is hardly recognizable in the US series (see Figure 3.C.6).

We re-estimate our baseline regression with the rolling ΔCoVaR as dependent variable. As shown in columns 6 and 7 of Table 3.8, there is a significant increase in systemic risk in all bubble episodes, as in our baseline regressions. The magnitudes are higher for real estate bubbles and slightly lower for stock market bubbles. While some of the further variables experience changes in their significance levels, the overall results are again robust.

3.6.2 Large and small banks

In a next step, we analyze whether the results differ between large and small banks. This distinction serves three purposes. First, as mentioned in Section 3.3, the dataset is dominated by relatively small banks, which are mostly located in the US (see Table 3.C.2). Small US banks are much more frequently listed than, for example, small European banks. Therefore, this robustness check can also rule out that our results are driven by small US banks. Second, in the baseline regressions, we assume that a bank is affected only by a bubble in its home country. For large and internationally active banks, this assumption may be rather strong. A focus on small, locally active banks allows us to address this potential concern because for them the assumption is more appropriate. Third, small and large banks display different business models and dynamics, which might not be fully captured by bank fixed effects and the bank size variable.

We split the sample into large and small banks. In order to avoid banks switching groups over time, the split is based on banks' mean size over the sample period. Banks with a mean size below (above) 30 billion USD are classified as small (large). The results are robust to the choice of the cut-off value. While the dominance of US banks is mitigated substantially in the sample of large banks, this is not true for the sample of small banks. Therefore, we drop the smallest US banks (again based on mean bank size) such that the number of observations from the US is no larger than that of the country with the second largest number of observations on small banks (France).

Table 3.9 displays the results for large (columns 1 and 2) and small banks (columns 3 and 4) separately. In each of the two samples, banks with median characteristics experience a significant increase in systemic risk during real estate busts as well as during stock market bubbles. However, this increase is much more pronounced in the sample of large banks. During real estate booms, a median bank's increase in systemic risk is statistically significant only in the sample of small banks (column 4). These findings are in line with our baseline results, in particular those on the interactions of bubble indicators with bank size. As argued above, this result may be due to mortgage lending being a core activity of small banks while large banks' business models are more diversified. While the increase in systemic risk contributions of small banks is larger during real estate booms, large banks again show a larger level of systemic risk throughout.[24] Hence, the activities of small banks deserve enhanced attention during real estate booms, but large banks remain more important from a financial stability perspective. While some of the other coefficients lose significance, possibly due to

[24] See the positive sum of the coefficients of bank size and its interaction with the bubble indicators.

the strongly reduced sample size, the results for both bank groups are very similar to our baseline regression. We can thus exclude that our results are driven by small banks or by the large number of US observations. Moreover, our previous results do not appear to be driven by asset price bubbles emerging outside of their home country, as they equally apply to small banks, which are only locally active.

As a further robustness check, we re-run our baseline regressions including the full sample of banks, weighting each bank's observations with their mean bank size relative to the size of their financial system. Thereby, we simultaneously limit the relevance of observations of small banks and eliminate the US bias in our sample. The results are reported in Table 3.9 (columns 5 and 6). While the increase in systemic risk during real estate booms again turns insignificant at median bank and bubble characteristics (similar to columns 1 and 2), the general results are once more in line with our previous findings. Overall, our results do not seem to be driven by banks of particular size.

Table 3.9: Large and small banks

Bubble estimates are based on the BSADF approach. Columns 1 to 4 provide estimates of our baseline regressions for small and large banks separately. We eliminate the US bias in the sample of small banks by excluding the smallest US banks. See Table 3.C.2 for an overview of the number of banks and observations per country. Columns 5 and 6 provide estimates from regressions with each bank's observations weighted by their mean bank size relative to the size of their financial system (North America, Europe, Japan, or Australia). Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Large banks		Small banks		Weighted by size	
Dependent variable:			ΔCoVaR			
Real estate boom	-0.01	0.07	0.06	0.10**	-0.13	-0.03
	(0.904)	(0.428)	(0.303)	(0.041)	(0.335)	(0.831)
Real estate bust	0.65***	0.67***	0.22***	0.23***	0.51**	0.51**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.014)	(0.013)
Stock boom	0.68***	0.64***	0.30***	0.26***	0.57***	0.55***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.82***	0.82***	0.37***	0.36***	0.71***	0.73***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.56***	0.55***	0.31***	0.30***	0.59***	0.54***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.07	-0.10*	-0.00	-0.01	-0.00	-0.03
	(0.138)	(0.057)	(0.891)	(0.801)	(0.975)	(0.463)
log(Bank size) · Real estate bust	0.22**	0.16	0.11**	0.11**	0.33***	0.30***
	(0.030)	(0.128)	(0.020)	(0.029)	(0.000)	(0.002)
log(Bank size) · Stock boom	0.03	0.06	0.07**	0.08***	0.07*	0.09**
	(0.582)	(0.293)	(0.013)	(0.005)	(0.064)	(0.027)
log(Bank size) · Stock bust	0.10**	0.10**	0.11***	0.11***	0.11***	0.12***
	(0.026)	(0.048)	(0.001)	(0.001)	(0.005)	(0.003)

(*table continued on next page*)

Table 3.9 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Large banks		Small banks		Weighted by size	
Dependent variable:			ΔCoVaR			
Loan growth	-5.61***	-5.89***	-0.68	-0.82	-4.16*	-4.40**
	(0.003)	(0.002)	(0.343)	(0.256)	(0.055)	(0.049)
Loan growth · Real estate boom	2.29	2.75	0.23	0.39	3.54	4.59
	(0.233)	(0.172)	(0.773)	(0.625)	(0.201)	(0.125)
Loan growth · Real estate bust	14.09***	15.68***	3.09	2.44	9.61**	11.47***
	(0.000)	(0.000)	(0.155)	(0.243)	(0.013)	(0.003)
Loan growth · Stock boom	2.28	2.00	-0.57	-0.53	-0.84	-0.88
	(0.222)	(0.282)	(0.554)	(0.602)	(0.722)	(0.722)
Loan growth · Stock bust	5.18*	6.44**	0.04	-0.11	3.15	3.17
	(0.054)	(0.017)	(0.977)	(0.945)	(0.297)	(0.298)
Leverage	0.02**	0.02**	0.00	0.00	0.03**	0.02**
	(0.023)	(0.025)	(0.711)	(0.500)	(0.026)	(0.048)
Leverage · Real estate boom	0.00	0.01	-0.01	-0.01	0.02	0.02*
	(0.733)	(0.468)	(0.144)	(0.104)	(0.173)	(0.097)
Leverage · Real estate bust	-0.04***	-0.03**	0.01	0.01	-0.02	-0.01
	(0.004)	(0.012)	(0.178)	(0.160)	(0.275)	(0.423)
Leverage · Stock boom	-0.02**	-0.02***	-0.01	-0.01*	-0.02**	-0.02***
	(0.015)	(0.003)	(0.179)	(0.063)	(0.017)	(0.004)
Leverage · Stock bust	-0.03***	-0.03***	-0.01***	-0.01***	-0.03***	-0.03***
	(0.000)	(0.000)	(0.010)	(0.005)	(0.001)	(0.002)
Maturity mismatch	-0.84**	-0.80**	-0.46***	-0.49***	-1.12***	-1.23***
	(0.038)	(0.047)	(0.008)	(0.004)	(0.008)	(0.004)
MM · Real estate boom	0.14	0.22	0.35***	0.38***	0.49	0.56
	(0.604)	(0.397)	(0.006)	(0.004)	(0.273)	(0.196)
MM · Real estate bust	0.54	0.69	-0.02	0.04	0.70	0.90
	(0.396)	(0.300)	(0.931)	(0.838)	(0.351)	(0.242)
MM · Stock boom	0.73**	0.84**	0.13	0.20	0.70*	0.73**
	(0.022)	(0.010)	(0.415)	(0.235)	(0.077)	(0.047)
MM · Stock bust	0.55**	0.66**	-0.02	0.05	0.37	0.57
	(0.040)	(0.025)	(0.921)	(0.735)	(0.364)	(0.209)
Real estate boom length	-0.02		-0.01		-0.04**	
	(0.278)		(0.138)		(0.015)	
Real estate boom size		0.00		-0.01		-0.03
		(0.882)		(0.486)		(0.191)
Real estate bust length	-0.19***		-0.07***		-0.15**	
	(0.000)		(0.001)		(0.010)	
Real estate bust size		-0.28***		-0.21**		-0.26***
		(0.001)		(0.011)		(0.009)
Stock boom length	0.32***		0.15***		0.33***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.07***		0.02***		0.08***
		(0.000)		(0.003)		(0.000)
Stock bust length	-0.36***		-0.10*		-0.30*	
	(0.009)		(0.057)		(0.093)	
Stock bust size		-0.08		-0.04		-0.05
		(0.575)		(0.586)		(0.766)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	28,916	28,916	31,400	31,400	165,149	165,149
Adj. R^2	0.589	0.585	0.817	0.815	0.655	0.652
Adj. R^2 within	0.202	0.194	0.139	0.132	0.204	0.196

3.6.3 Choice of sample period

We then re-estimate our baseline regressions for different sample periods to exclude that the results are driven by particular bubble episodes. First, we run the regressions excluding observations before 1995, as the number of banks is relatively small in the beginning of our sample, which may make this period less representative. As shown in Table 3.10, the results are highly robust to the exclusion of the initial period of our sample (columns 1 and 2). While the relationship between systemic risk and real estate booms turns insignificant at median bank and bubble characteristics, the signs and significance levels of all other coefficients are almost always identical to the baseline regression shown in Table 3.4, columns 3 and 4.

Table 3.10: Choice of sample period and additional control for business cycle

Columns 1 to 4 restrict the sample period as indicated. Columns 5 and 6 add a business cycle indicator to our baseline specification. Bubble estimates are based on the BSADF approach. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	>1995m1		≠2008		Full sample	
Dependent variable:			ΔCoVaR			
Real estate boom	0.03	0.06	0.12***	0.14***	0.11***	0.13***
	(0.455)	(0.139)	(0.000)	(0.000)	(0.003)	(0.000)
Real estate bust	0.22*	0.25**	0.39***	0.40***	0.22*	0.25**
	(0.084)	(0.045)	(0.000)	(0.000)	(0.069)	(0.037)
Stock boom	0.30***	0.33***	0.30***	0.31***	0.38***	0.40***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.36***	0.35***	0.43***	0.42***	0.29***	0.28***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
log(Bank size)	0.22***	0.22***	0.17***	0.16***	0.27***	0.27***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.02	-0.02	0.01	0.01	-0.01	-0.01
	(0.287)	(0.280)	(0.644)	(0.634)	(0.494)	(0.465)
log(Bank size) · Real estate bust	0.17***	0.16***	0.13***	0.12***	0.18***	0.17***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.06**	0.05**	0.08***	0.07***	0.06***	0.06***
	(0.012)	(0.021)	(0.000)	(0.000)	(0.002)	(0.004)
log(Bank size) · Stock bust	0.11***	0.11***	0.12***	0.12***	0.12***	0.12***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.24*	-1.34**	-1.67***	-1.83***	-1.78***	-1.87***
	(0.066)	(0.049)	(0.000)	(0.000)	(0.005)	(0.003)
Loan growth · Real estate boom	1.40*	1.55**	0.87	1.09*	2.02***	2.12***
	(0.062)	(0.041)	(0.108)	(0.050)	(0.005)	(0.003)
Loan growth · Real estate bust	4.79***	4.89***	5.25***	5.58***	4.61***	4.59***
	(0.001)	(0.001)	(0.006)	(0.003)	(0.002)	(0.002)
Loan growth · Stock boom	0.78	0.93	1.29**	1.48**	0.86	1.01
	(0.243)	(0.183)	(0.033)	(0.018)	(0.206)	(0.155)
Loan growth · Stock bust	2.45***	2.66***	2.98***	3.11***	2.74***	2.90***
	(0.005)	(0.003)	(0.001)	(0.000)	(0.001)	(0.001)

(*table continued on next page*)

Table 3.10 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	>1995m1		≠2008		Full sample	
Dependent variable:			ΔCoVaR			
Leverage	0.00	0.00	0.00*	0.00**	0.00*	0.00*
	(0.147)	(0.166)	(0.054)	(0.047)	(0.072)	(0.071)
Leverage · Real estate boom	0.01***	0.01***	0.01*	0.01*	0.01**	0.01**
	(0.010)	(0.007)	(0.075)	(0.063)	(0.030)	(0.028)
Leverage · Real estate bust	-0.01	-0.00	-0.01	-0.01	-0.01*	-0.01
	(0.431)	(0.644)	(0.134)	(0.190)	(0.083)	(0.135)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.006)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch	-0.55***	-0.52***	-0.55***	-0.55***	-0.60***	-0.59***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.11	0.07	0.22***	0.22**	0.19**	0.18**
	(0.215)	(0.414)	(0.009)	(0.010)	(0.044)	(0.049)
MM · Real estate bust	0.26	0.35	0.52**	0.58**	0.26	0.34
	(0.245)	(0.122)	(0.017)	(0.011)	(0.226)	(0.121)
MM · Stock boom	0.32***	0.43***	0.35***	0.46***	0.39***	0.49***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.29**	0.43***	0.34***	0.43***	0.21	0.32**
	(0.030)	(0.001)	(0.005)	(0.000)	(0.137)	(0.015)
Real estate boom length	-0.01		-0.00		0.00	
	(0.318)		(0.509)		(0.922)	
Real estate boom size		0.00		0.00		0.01
		(0.849)		(0.940)		(0.300)
Real estate bust length	-0.17***		-0.09**		-0.15***	
	(0.000)		(0.017)		(0.000)	
Real estate bust size		-0.30***		-0.13**		-0.28***
		(0.004)		(0.036)		(0.005)
Stock boom length	0.18***		0.15***		0.18***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.04***		0.03***		0.04***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.35***		-0.26***		-0.33***	
	(0.000)		(0.003)		(0.001)	
Stock bust size		-0.14*		-0.10		-0.13
		(0.092)		(0.196)		(0.120)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Business Cycle	No	No	No	No	Yes	Yes
No. of obs.	157,910	157,910	156,468	156,468	165,149	165,149
Adj. R^2	0.834	0.833	0.884	0.883	0.833	0.832
Adj. R^2 within	0.132	0.125	0.153	0.144	0.153	0.148

Second, one may worry that the results are unduly affected by the global financial crisis. Moreover, real estate bubbles are more frequent during the second half of our sample. One might be concerned about a structural break leading to both the occurrence of real estate bubbles and increased systemic risk. A visual inspection of Figure 3.4, which displays the development of ΔCoVaR over time, does not reveal a general increase in systemic risk when abstracting from the financial crisis. Excluding the global financial crisis yields an even stronger relationship between systemic risk and real estate busts (Table 3.10, columns 3 and 4). The remaining results are again highly robust. Consequently, none of our results appears to be driven by these particular bubble episodes.

3.6.4 Business cycles

In a final robustness check, we attempt to better account for business cycles. In our regressions, we take account of the development of the real economy by controlling for GDP growth. However, this variable may not fully capture business cycles. While parts of the recent literature have argued that business cycles and financial cycles have become less connected in recent years (e. g., Drehmann, Borio, and Tsatsaronis, 2012), this may not be true for our entire sample. Therefore, we use data on turning points of business cycles provided by the OECD to construct an indicator variable that equals one during the boom phase of the business cycle, and zero otherwise.

We plot business cycles alongside bubble boom and bust episodes. The visual inspection reveals no significant synchronization between business and financial cycles (see Figure 3.C.7). In fact, business cycle booms exhibit a small negative correlation with stock market and real estate booms in our sample (see Table 3.C.13, columns 1 and 3). As an additional check, we re-estimate our baseline regressions including the business cycle boom indicator. Only few coefficients change their significance levels, and all main results continue to hold, which confirms our previous findings (see Table 3.10, columns 5 and 6).

3.7 Conclusion

Employing a broad sample of banks in 17 OECD countries over the period 1987 to 2015, this paper empirically analyzes the relationship between asset price bubbles and systemic risk. While most of the previous empirical literature has approached this question at macroeconomic level, we provide evidence on the relationship between asset price bubbles and systemic risk at the level of individual financial institutions. This allows us to assess the allocation of risks across banks, which is crucial for detecting the sources of financial fragility and can inform regulators and supervisors which banks deserve particular attention with respect to asset price bubbles.

Our results show that asset price bubbles are indeed associated with higher systemic risk at bank level. This relationship is not limited to the turmoil following the burst of a bubble, but it exists already during its emergence. The increase in systemic risk depends strongly on bank characteristics. Higher loan growth, a stronger maturity mismatch, and especially larger bank size tend to make financial institutions, and hence the financial system, more vulnerable to asset price bubbles. Only in real estate booms, it is the small banks which tend to experience larger increases in systemic risk. This is likely to be related to their stronger focus on mortgage lending. The size and length of asset price booms and busts matter as well. The increase in systemic risk is largest during real estate busts, especially for banks with unfavorable characteristics: The 95^{th} percentile of the increase in systemic risk in dependence of bank characteristics is equal to 55 percent of the median of ΔCoVaR, the 99^{th} percentile to almost 70 percent. To put the economic significance of the systemic risk increase further into perspective, a back of the envelope calculation for the burst of the US subprime housing bubble shows that the systemic risk posed by the distress of Lehman Brothers would have been 40 percent lower if the bubble had not existed.

The main results are very similar across different bubble and systemic risk measures, with a few exceptions. Real estate booms appear less problematic at median bank and bubble characteristics when using a trend-deviation approach for bubble identification, or MES instead of ΔCoVaR as a measure of systemic risk. However, all types of bubbles still show sharp increases in systemic risk for unfavorable bank characteristics. Moreover, the specific relationship with some bank characteristics changes in the regressions using MES in line with the conceptual differences between the two measures. But as with ΔCoVaR, busts show larger increases in systemic risk than booms, and the increases are strongly related to banks' characteristics, especially bank size. When accounting for ΔCoVaR's dependence on aggregate equity market returns and volatilities, the increase in systemic risk during stock market bubbles becomes smaller. Our results are not driven by particular episodes, such as the US subprime housing bubble and the following global financial crisis, nor by business cycle effects. Neither are they specific to certain countries or a particular group of banks. Hence, the results appear to be robust across a broad range of robustness checks.

While we do not explicitly analyze the role of financial regulation, our results suggest a number of policy implications from a financial stability perspective. First, and most importantly, our results suggest that policies at macroeconomic level are insufficient to deal with asset price bubbles, because an important part of the vulnerability stems from the differences across banks. According to our analysis, the adverse effects of bubbles may be mitigated substantially by strengthening the resilience of financial institutions. Large banks deserve particular attention. The strong relationship between bank size and increases in systemic risk during bubble episodes may justify bank structural reforms trying to contain bank size. Second, intervening only after a bubble has burst ("cleaning up the mess") may be overly costly. Systemic risk rises already in the boom phase and it appears well-advisable to counteract such a build-up of systemic risk early on in order to avoid a harmful collapse at later stages. In fact, bubble size and length play a noticeable role in the build-up of systemic risk, especially in stock market booms. However, such policy measures are much harder to implement because they require identifying asset price bubbles in real time. Finally, stock market bubbles cannot entirely be dismissed as a source of financial instability because their fallout may be substantial as well, especially for weak bank characteristics. While causal relationships are hard to establish in a clear-cut way, our analysis is highly suggestive that policies focusing on the resilience of financial institutions starting preferably already in the boom phase carry the promise of substantially contributing to a more stable financial system.

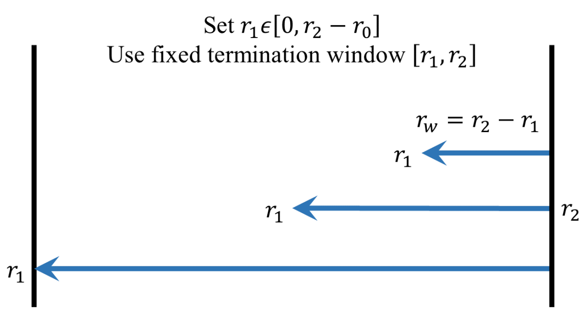
3.A Appendix: estimation of bubble episodes

The BSADF approach applies sequences of ADF tests to systematically changing fractions of a sample to identify episodes of explosive processes in price data. We follow the estimation strategy proposed by Phillips, Shi, and Yu (2015a). To fix notation, let r_1 denote some starting fraction of the sample and r_2 some ending fraction, implying $r_1 < r_2$. The fraction of the corresponding subsample is given by $r_w = r_2 - r_1$. Furthermore, let r_0 denote the fractional threshold that ensures that any analyzed subsample is large enough for the test to be efficient. The threshold is chosen according to $r_0 = 0.01 + 1.8\sqrt{T}$, where T refers to the number of observations in the sample.

The BSADF statistic (as opposed to the approach) for sample fraction r_2 is given by the supremum of all values of the test statistics of ADF tests performed while holding the ending fraction of the sample fixed at r_2 and varying the starting fraction from 0 to $r_2 - r_0$. Figure 3.A.1 illustrates the idea. Formally, the BSADF statistic is thus given by

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \left\{ BADF_{r_1}^{r_2} \right\} . \tag{3.5}$$

Figure 3.A.1: Recursive nature of the BSADF test



Source: Phillips, Shi, and Yu (2015a, p. 1052)

The identification of bubble episodes relies on a sequence of BSADF statistics resulting from varying ending fraction r_2. Let the fraction of the sample at which the bubble starts be denoted by r_e, the fraction of the sample at which it ends by r_f, and the estimators of both by $\hat{r}_e$ and $\hat{r}_f$, respectively. The starting fraction r_e is estimated by the earliest point in time for which the BSADF test rejects the null hypothesis of no bubble existing. Similarly, the estimator for ending fraction r_f is given by the earliest point in time after the emergence of the bubble and some minimum bubble length $\delta log(T)$ for which the BSADF test does not reject the null. Formally,

$$\hat{r}_e = \inf_{r_2 \in [r_0,1]} [r_2 : BSADF_{r_2}(r_0) > scv_{r_2}^{\beta}] \tag{3.6}$$

$$\text{and } \hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta log(T),1]} [r_2 : BSADF_{r_2}(r_0) < scv_{r_2}^{\beta}] \,, \tag{3.7}$$

where T is the number of observations of the analyzed time series and $scv_{r_2}^{\beta}$ is the critical value of the BSADF statistic based on $\lfloor Tr_2 \rfloor$ observations and confidence level β. $\lfloor Tr_2 \rfloor$ refers to the largest integer smaller than or equal to Tr_2. Critical values are obtained by Monte Carlo simulations based on 2,000 repetitions. The parameter δ is to be chosen freely according to one's beliefs about what minimum duration should be required in order to call surging prices a bubble. The minimum length requirement excludes short blips from being identified as bubbles and prevents estimating an overly early termination date. We choose δ such that the minimum length of bubbles equals 6 months. The test identifies a few instances of bust-boom cycles that might be interpreted as "negative bubbles." Unfortunately, their number is too low to be included as a separate category in the main analyses. As the dynamics during such bust-boom cycles are likely to be quite different from those during customary bubble episodes, we disregard these bust-boom episodes when constructing the bubble indicators.

3.B Appendix: estimation of ΔCoVaR

We obtain daily information on the number of outstanding shares, unpadded unadjusted prices of common equity in national currency, and the corresponding market capitalization in US Dollar from Thomson Reuters Datastream. To exclude public offerings, repurchases of shares and similar activities from biasing the results, observations for which the number of outstanding shares changed compared to the previous day are dropped. The daily observations are then collapsed to weekly frequency.

We calculate the weekly return losses on equity (X) of institution i and those of the financial system:

$$X^i_{t+1} = -\frac{P^i_{t+1}N^i_{t+1} - P^i_t N^i_t}{P^i_t N^i_t} \text{ and} \tag{3.8}$$

$$X^{system}_{t+1} = \sum_i \frac{MV^i_t}{\sum_i MV^i_t} X^i_{t+1}\,, \tag{3.9}$$

where P^i_t is the price of common equity of institution i at time t in national currency, N refers to the number of outstanding shares and MV is the market value in US Dollar. We use national currencies to compute the return losses in Equation (3.8) to prevent exchange rate fluctuations from biasing our results.[25] When calculating market shares of each institution (the ratio in Equation (3.9)), we have to rely on a uniform currency, which is why we use the market values in US dollar there. While exchange rate fluctuations introduce noise into the calculation of system return losses, they do not bias the results.

The return losses are merged with variables capturing general risk factors. Adrian and Brunnermeier (2016) use the following state variables:

- the change in the three-month yield calculated from the three-month T-Bill rate published with the Federal Reserve Board's H.15 release;
- the change in the slope of the yield curve as captured by the yield spread between the ten-year treasury rate (FRB H.15) and the three-month T-Bill rate;
- the TED spread, measured as the difference between the three-month Libor rate (FRED database) and the three-month secondary market bill rate (FRB H.15);
- the change in the credit spread between the bonds obtaining a Baa rating from Moody's (FRB H.15) and the ten-year treasury rate;
- the weekly market returns of the S&P 500;
- the equity volatility calculated as a 22-day rolling window standard deviation of the daily CRSP equity market return;

[25] To clarify the relevance of the currency, suppose return losses of Eurozone banks were calculated in US dollar. Further suppose, the euro would depreciate vis-à-vis the US dollar. Then, all other things equal, all banks in the Eurozone would simultaneously experience return losses which would lead to increases in ΔCoVaR.

- the difference between the weekly real estate sector return (companies with a SIC code between 65 and 66) and the weekly financial system return (all financial companies in the sample).

As usual for the estimation of ΔCoVaR outside the US, we do not include the spread between the real estate sector return and the financial system return.[26] Since we estimate ΔCoVaR in a multi-country setting, we assign each financial institution to one of the following four financial systems: North America, Europe, Japan or Australia. The association with a system is based on the location of an institution's headquarter. We use a distinct set of state variables for each system. Table 3.B.1 provides an overview of the data used to construct the system-specific control variables.

The estimation procedure starts by estimating the VaR and the relationship between institution-specific losses and system losses using the following quantile regressions:[27]

$$\widehat{VaR}^{i}_{q,t} = \hat{X}^{i}_{q,t} = \hat{\alpha}^{i}_{q} + \hat{\gamma}^{i}_{q} M_{t-1} \,, \tag{3.10}$$

$$\hat{X}^{system|i}_{q,t} = \hat{\alpha}^{system|i}_{q} + \hat{\gamma}^{system|i}_{q} M_{t-1} + \hat{\beta}^{system|i}_{q} X^{i}_{t} \,. \tag{3.11}$$

M_{t-1} is a vector of the macroeconomic control variables. We apply a stress level of $q = 98\%$ in all regressions. The conditional value at risk is calculated by combining estimates from the two previous regressions:

$$CoVaR^{i}_{q,t} = \hat{\alpha}^{system|i}_{q} + \hat{\gamma}^{system|i}_{q} M_{t-1} + \hat{\beta}^{system|i}_{q} \widehat{VaR}^{i}_{q,t} \,. \tag{3.12}$$

Following the definition provided in Equation (3.1), the time series of ΔCoVaR is calculated as

$$\Delta CoVaR^{i}_{q,t} = \hat{\beta}^{system|i}_{q} (\widehat{VaR}^{i}_{q,t} - \widehat{VaR}^{i}_{50,t}) \,. \tag{3.13}$$

[26] See, e. g., López-Espinosa et al. (2012) and Barth and Schnabel (2013).

[27] For a detailed exposition of quantile regressions, see Koenker (2005). The literature suggests a number of alternative estimation techniques: MGARCH (Girardi and Tolga Ergün, 2013), copulas (Mainik and Schaanning, 2012; Oh and Patton, 2015), maximum likelihood (Cao, 2013), and Bayesian inference (Bernardi, Gayraud, and Petrella, 2013). All of these alternative approaches are less frequently applied than the quantile regression approach.

We estimate ΔCoVaR at weekly frequency. To merge them with all other variables included in our main analyses, we collapse the resulting estimates to monthly frequency by taking averages.

Table 3.B.1: System-specific data

The 10-year government bond rates for Germany, Japan and Australia are only available at monthly frequency. In these instances, we use cubic spline interpolations to obtain the weekly observations required for the quantile regressions.

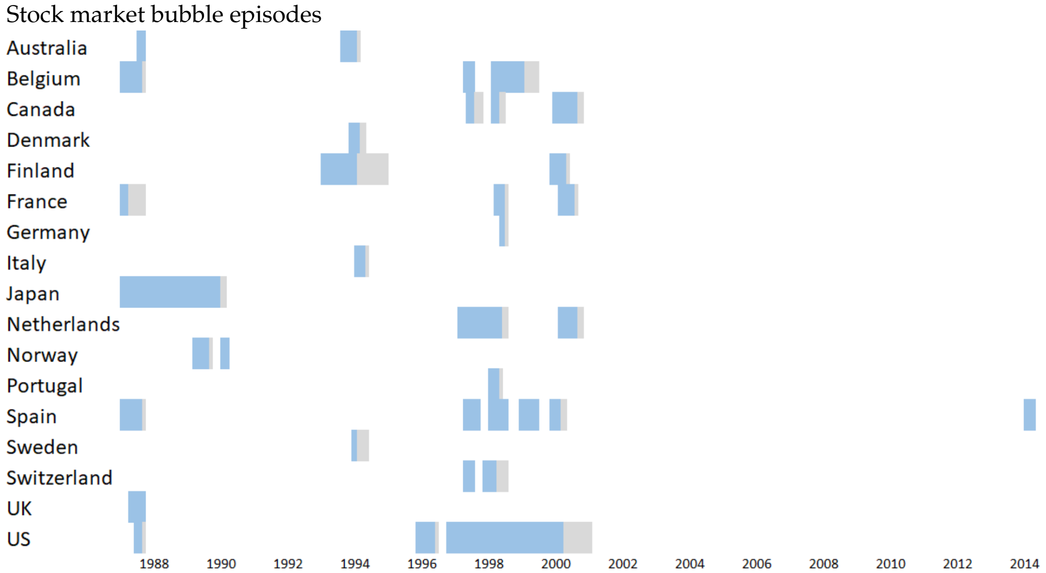
Adrian and Brunnermeier 2016	**Data used instead**			
	North America	**Europe**	**Japan**	**Australia**
10Y treasury rate	US 10Y treasury rate (FRED)	German 10Y govt. bond rate (OECD)	Japanese 10Y govt. bond rate (OECD)	Australian 10Y govt. bond rate (OECD)
3M T-Bill rate	US 3M T-Bill rate (FRED)	German 3M govt. bond rate (Bloomberg, FRED)	Japanese 3M govt. bond rate (Bloomberg, FRED)	Australian 3M govt. bond rate (Bloomberg, FRED)
3M Libor rate	3M Libor rate (FRED)	3M Fibor and 3M Euribor rate (Datastream)	3M Japanese Libor rate (FRED)	Australian 3M interbank rate (Datastream)
Moody's Baa rated bonds	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)	Moody's Baa rated bonds (FRED)
S&P500	MSCI North America (Datastream)	MSCI Europe (Datastream)	MSCI Japan (Datastream)	MSCI Australia (Datastream)
CRSP equity market index	MSCI North America (Datastream)	MSCI Europe (Datastream)	MSCI Japan (Datastream)	MSCI Australia (Datastream)

3.C Appendix: additional figures and tables

Figure 3.C.1: Bubble episodes by country and asset class: normalized price data

Periods colored in blue represent the boom phase of an asset price bubble, periods in grey refer to the bust phase of a bubble. Bubble episodes are estimated based on the BSADF approach using price-to-dividend and price-to-rent data. For details on the estimation procedure see Section 3.3.2 and Appendix 3.A. Panel B of Table 3.1 reports correlations across the bubble indicators resulting from the three different identification approaches.

(a) Stock market bubble episodes



(b) Real estate bubble episodes

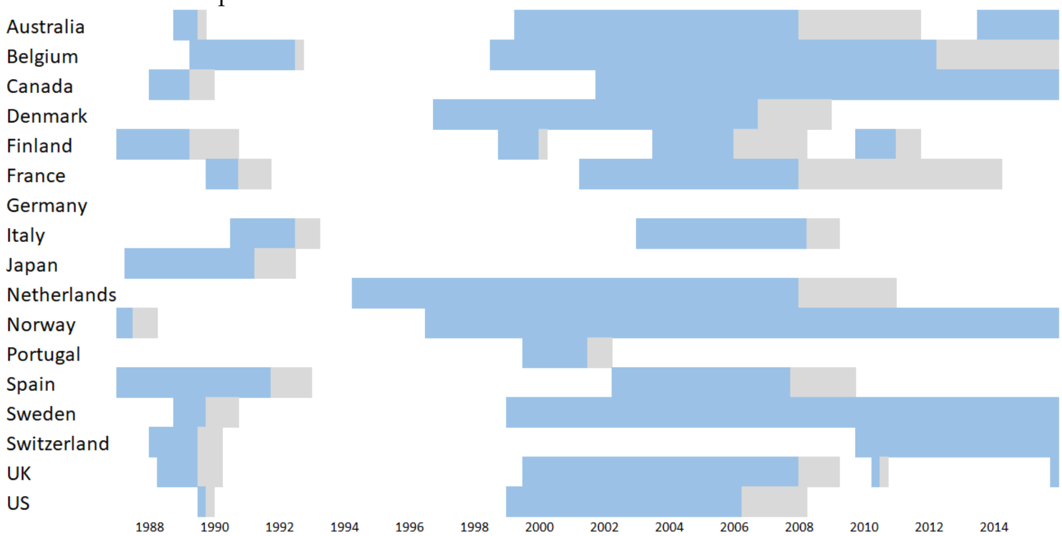
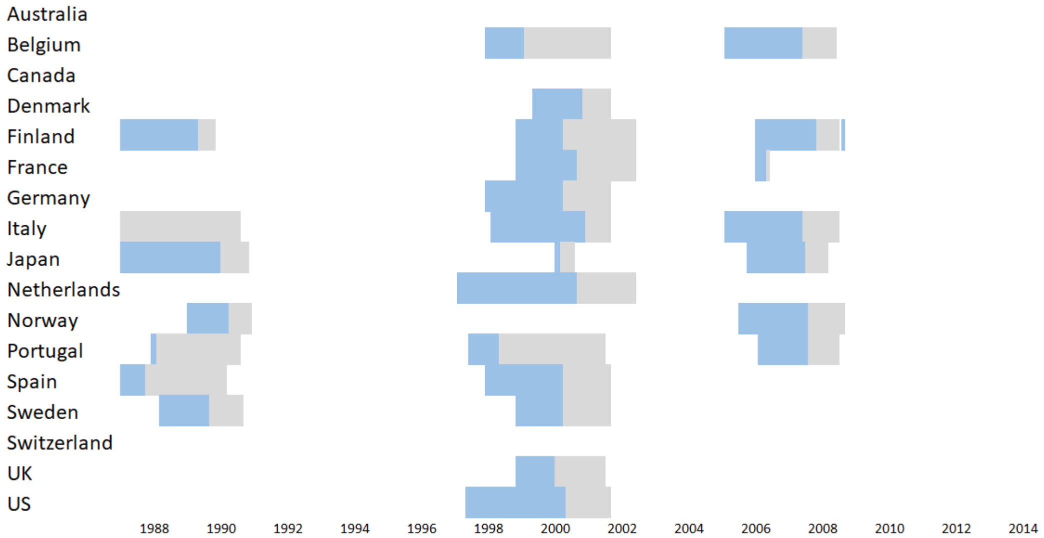


Figure 3.C.2: Bubble episodes by country and asset class: trend-deviation approach

Periods colored in blue represent the boom phase of an asset price bubble, periods in grey refer to the bust phase of a bubble. Bubble episodes are estimated following the trend-deviation approach in Jordà, Schularick, and Taylor (2015b). For details on the estimation procedure see Section 3.3.2. Panel B of Table 3.1 reports correlations across the bubble indicators resulting from the three different identification approaches.

(a) Stock market bubble episodes



(b) Real estate bubble episodes

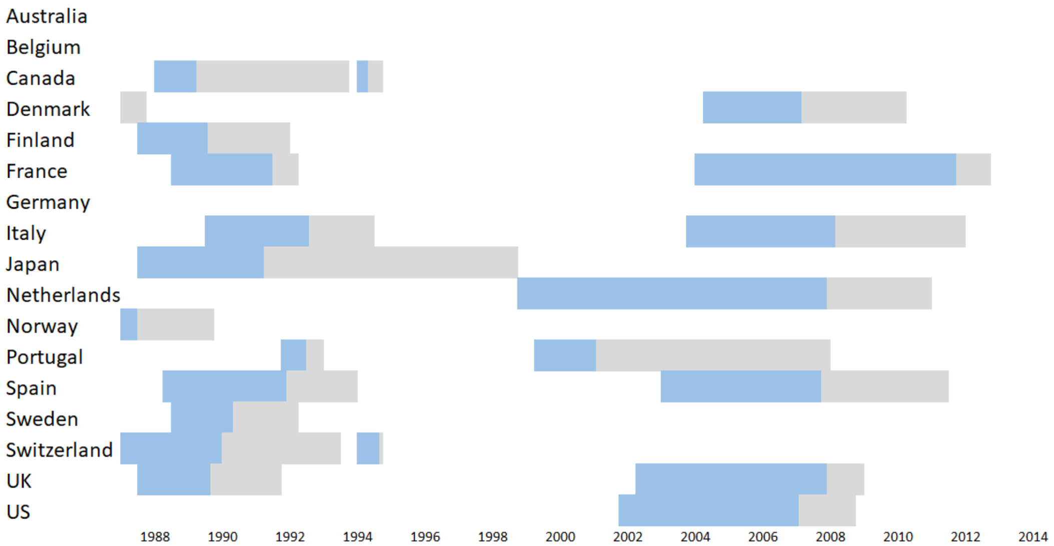


Figure 3.C.3: Systemic risk during bubble episodes: normalized price data

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔCoVaR. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. The results rely on the average of the estimated coefficients in Table 3.6, columns 3 and 4. For these regressions, bubble episodes are identified by applying the BSADF approach to price-to-dividend and price-to-rent data. The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.

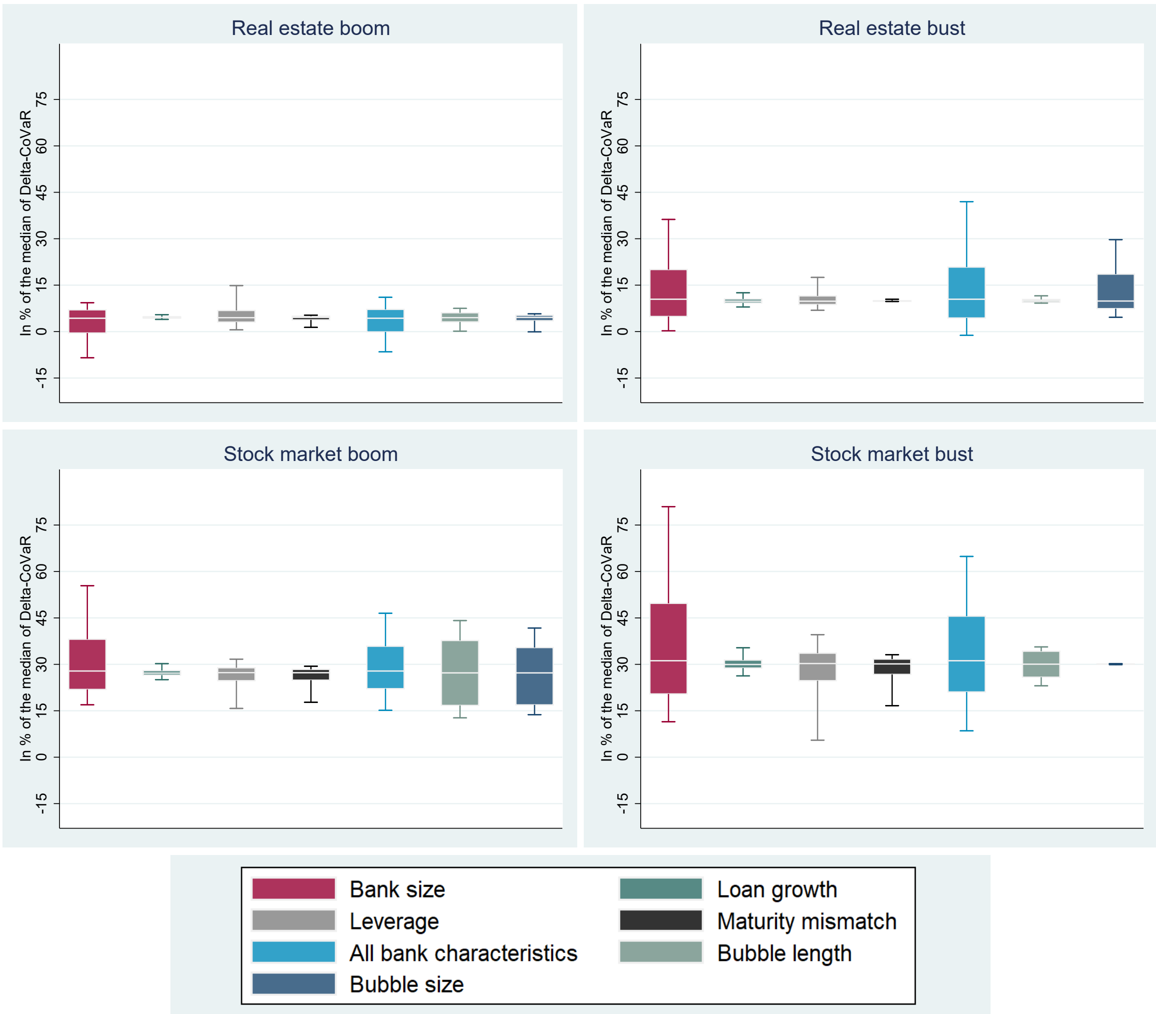


Figure 3.C.4: Systemic risk during bubble episodes: trend-deviation approach

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔCoVaR. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. The results rely on the average of the estimated coefficients in Table 3.6, columns 5 and 6. For these regressions, bubble episodes are identified based on the trend-deviation approach in Jordà, Schularick, and Taylor (2015b). The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.

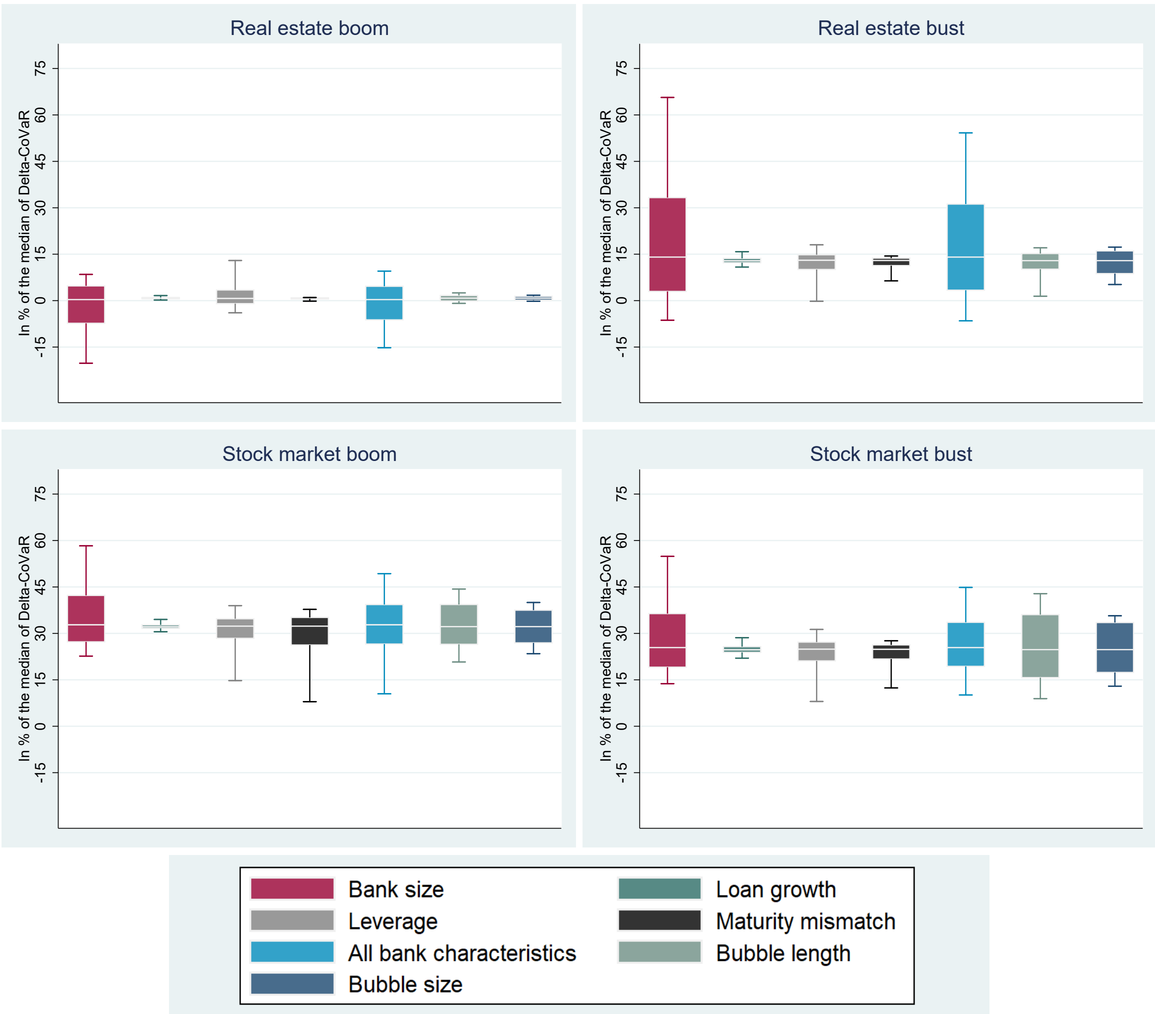


Figure 3.C.5: Systemic risk during bubble episodes: marginal expected shortfall

The figure illustrates the distribution of the increase in systemic risk during bubble episodes in percent of the median of ΔMES. The white horizontal line within each box refers to the increase at the median of all characteristics. The upper and lower end of the boxes refer to the increase at the 75^{th} and 25^{th} percentile of the distribution of the indicated bank or bubble characteristics. The upper and lower end of the lines refer to the 95^{th} and 5^{th} percentile. The results rely on the average of the estimated coefficients in Table 3.7, columns 6 and 7. The largest bank does not simultaneously exhibit the largest loan growth, leverage, and maturity mismatch, such that the range depending on all bank characteristics is smaller than the sum of the ranges of individual bank characteristics.

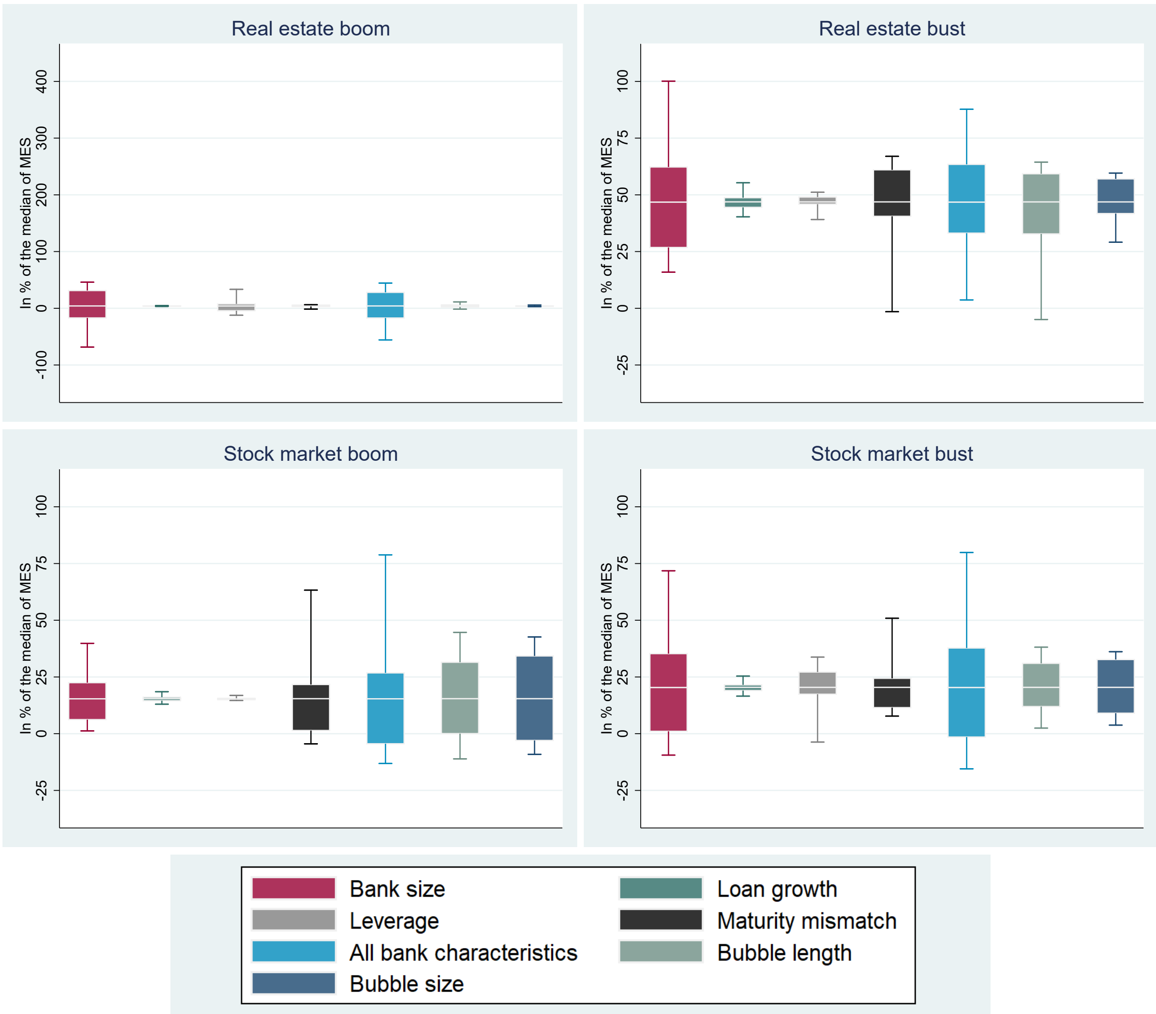


Figure 3.C.6: Evolution of ΔCoVaR and rolling ΔCoVaR over time

The figure displays the unweighted means of ΔCoVaR and the rolling ΔCoVaR in weekly percentage points for the four financial systems in our sample: North America, Europe, Japan, and Australia. Details on the estimation procedure of ΔCoVaR are provided in Section 3.3.3 and Appendix 3.B. The estimation procedure of the rolling ΔCoVaR is described in Section 3.6.1.

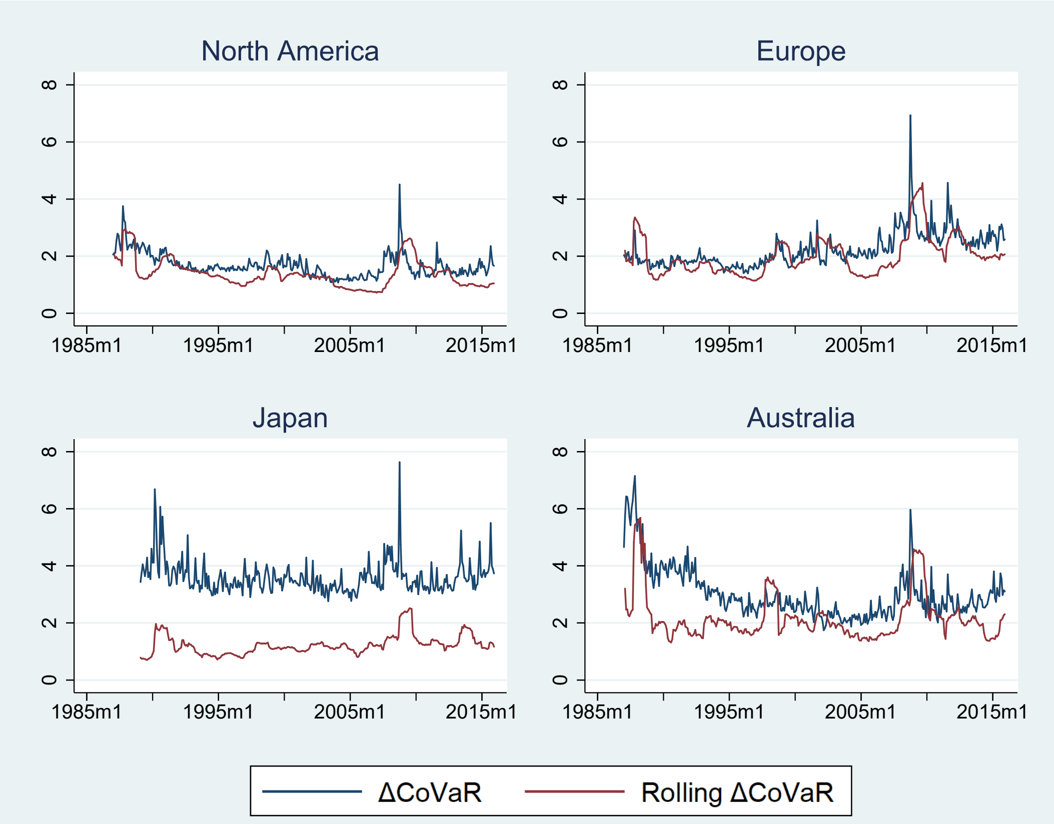
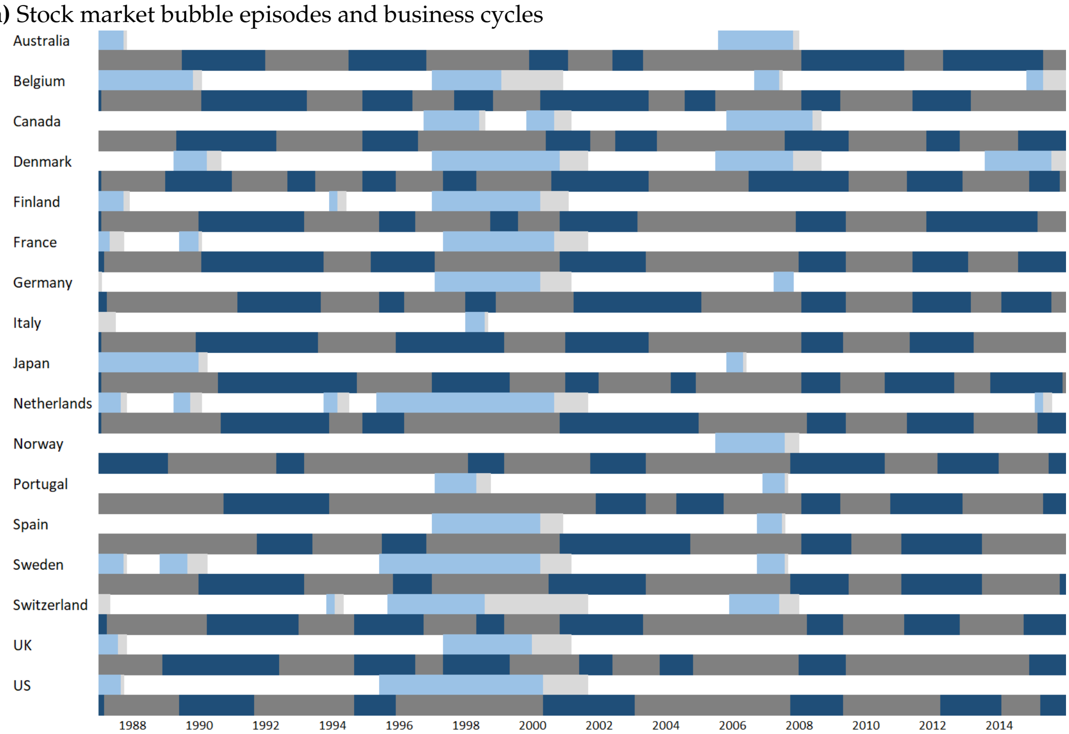


Figure 3.C.7: Bubble episodes by country and asset class: business cycles

Periods colored in light blue and light grey represent the boom and bust phase of asset price bubbles. Periods colored in dark blue and dark grey represent the boom and bust phase of the business cycle. Bubble episodes are estimated based on the BSADF approach. For details on the estimation procedure see Section 3.3.2 and Appendix 3.A.

(a) Stock market bubble episodes and business cycles



(b) Real estate bubble episodes and business cycles

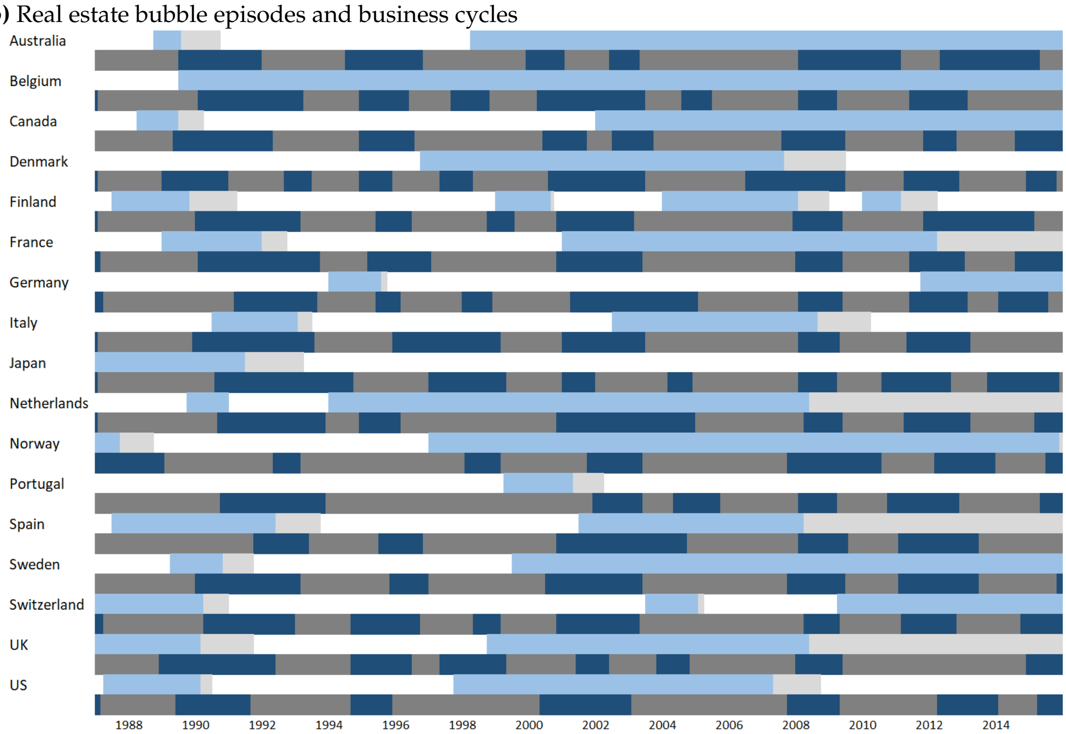


Table 3.C.1: Variable definitions and data sources

Detailed information on the variables' construction is provided in Sections 3.3, Appendix 3.A, and Appendix 3.B.

Variable name	Description
Dependent variable	
ΔCoVaR	Change in the conditional value at risk; estimation strategy provided in Section 3.3.3 and Appendix 3.B. Source of market equity data: Datastream. Sources of control variables: see Table 3.B.1.
MES	Marginal expected shortfall; winsorized at 1%/99%; estimation strategy provided in Section 3.3.3 Source of market equity data: Datastream.
Rolling ΔCoVaR	Rolling window version of ΔCoVaR (see above); estimation strategy provided in Section 3.6.1.
System-specific CoVaR variables	
Equity market returns	Weekly market returns of system-specific MSCI indices. Data sources: see Table 3.B.1.
Equity market volatility	22-day rolling window standard deviation of the daily system-specific MSCI indices. Data sources: see Table 3.B.1.
Change in the 3M yield	The change in three-month government bond rates. Data sources: see Table 3.B.1.
Change in the slope of the yield curve	The change in the yield spread between ten-year and three-month government bond rates. Data sources: see Table 3.B.1.
TED spread	The difference between three-month Libor rates and three-month government bond rates. Data sources: see Table 3.B.1.
Credit spread	The difference between Moody's Baa rated bonds and ten-year government bond rates. Data sources: see Table 3.B.1.
Bubble indicators	
Real estate boom	Country-specific binary indicator; equals one during the boom phase of a real estate bubble; estimated based on the BSADF approach or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.3.2). Source of real estate date: OECD.
Real estate bust	Country-specific binary indicator; equals one during the bust phase of a real estate bubble; estimated based on the BSADF approach or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.3.2). Source of real estate date: OECD.
Stock market boom	Country-specific binary indicator; equals one during the boom phase of a stock market bubble; estimated based on the BSADF approach or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.3.2). Source of stock market indeces: Datastream.
Stock market bust	Country-specific binary indicator; equals one during the bust phase of a stock market bubble; estimated based on the BSADF approach or following the strategy in Jordà, Schularick, and Taylor (2015b) (Section 3.3.2). Source of stock market indeces: Datastream.

(*table continued on next page*)

Table 3.C.1 - *continued*

Variable name	Description
Bubble characteristics	
Length	Four country-specific variables (length of real estate boom, real estate bust, stock market boom, stock market bust); time since the beginning or climax of the respective bubble phase and episode in years; equals zero outside of the respective bubble phase and episode (Section 3.3.2). Sources of the underlying data: OECD and Datastream.
Size	Four country-specific variables (size of real estate boom, real estate bust, stock market boom, stock market bust); size of an emerging bubble or size of its collapse in 10%; equals zero outside of bubble episodes (Section 3.3.2). Sources of the underlying data: OECD and Datastream.
Bank characteristics	
Bank size	log(total assets); winsorized at 1%/99%. Source: Bankscope.
Loan growth	Δlog(total loans); monthly growth rate of total loans excluding interbank lending; winsorized at 1%/99%. Source: Bankscope.
Leverage	Total assets/equity; winsorized at 1%/99%. Source: Bankscope.
Maturity mismatch (MM)	(Total deposits, money market and short-term funding – loans and advances to banks – cash and due from banks)/total assets; winsorized at 1%/99%. Source: Bankscope.
Macroeconomic variables	
Banking crisis	Country-specific binary indicator; equals one during a banking crisis; Source: Laeven and Valencia (2012), updated.
GDP growth	Δlog(real GDP); monthly growth rate. Source: OECD.
Interest rate	log(10-year government bond rate); Source: OECD.
Inflation	Δlog(CPI); monthly rate. Source: OECD.
Investment-to-GDP growth	Δlog(investment/GDP); monthly rate. Source: OECD.

Table 3.C.2: Sample coverage

The choice of countries is entirely determined by data availability. See Section 3.6.2 for robustness checks confirming that the results are not driven by a single country.

	Full sample			Large banks			Small banks		
Country	Banks	# Obs.	% Obs.	Banks	# Obs.	% Obs.	Banks	# Obs.	% Obs.
Australia	16	2,732	2	9	1,605	6	7	1,127	1
Belgium	5	597	0	3	514	2	2	83	0
Canada	14	1,976	1	9	1,662	6	5	314	0
Denmark	19	2,981	2	3	440	2	16	2,541	2
Finland	4	696	0	2	114	0	2	582	0
France	48	6,515	4	10	1,776	6	38	4,739	3
Germany	24	3,581	2	15	1,960	7	9	1,621	1
Italy	36	5,917	4	22	2,498	9	14	3,419	3
Japan	112	6,210	4	66	3,652	13	46	2,558	2
Netherlands	9	1,198	1	3	283	1	6	915	1
Norway	24	3,369	2	3	283	1	21	3,086	2
Portugal	7	969	1	3	341	1	4	628	0
Spain	14	2,724	2	10	1,588	6	4	1,136	1
Sweden	6	1,192	1	4	1,084	4	2	108	0
Switzerland	23	3,609	2	10	786	3	13	2,823	2
UK	20	3,633	2	12	2,233	8	8	1,400	1
US	883	117,250	71	59	7,493	26	824	109,757	80
Total	1,264	165,149	100	243	28,312	100	1,021	136,837	100

Table 3.C.3: Baseline regression without boom-bust distinction

Re-esimate of the baseline regression from Table 3.4, column 5, but without the boom-bust distinction. Bubble characteristics are left out as they were defined in dependence of the switch from boom to bust. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)
Dependent variable:	ΔCoVaR	
Real estate bubble	0.17***	0.17***
	(0.001)	(0.002)
Stock market bubble	0.37***	0.19***
	(0.000)	(0.000)
log(Bank size)	0.28***	0.05*
	(0.000)	(0.086)
log(Bank size) · Real estate bubble	0.02	0.01
	(0.244)	(0.645)
log(Bank size) · Stock market bubble	0.05***	0.06***
	(0.001)	(0.001)
Loan growth	-1.98***	-2.29***
	(0.004)	(0.000)
Loan growth · Real estate bubble	2.37***	2.62***
	(0.004)	(0.000)
Loan growth · Stock market bubble	2.29***	1.22**
	(0.002)	(0.033)
Leverage	0.00*	0.01**
	(0.076)	(0.010)
Leverage · Real estate bubble	0.00	0.00
	(0.412)	(0.623)
Leverage · Stock market bubble	-0.01***	-0.01***
	(0.000)	(0.000)
Maturity mismatch	-0.67***	-0.57***
	(0.000)	(0.000)
MM · Real estate bubble	0.28***	0.18**
	(0.003)	(0.029)
MM · Stock market bubble	0.51***	0.54***
	(0.000)	(0.000)
Bank FE	Yes	Yes
Time FE	No	Yes
Macro Controls	Yes	Yes
No. of obs.	165,149	165,149
Adj. R^2	0.824	0.873
Adj. R^2 within	0.107	0.028

Table 3.C.4: The role of bank and bubble characteristics: use of interpolated data

Columns 1 and 2 restate our baseline regressions from Table 3.4, columns 6 and 7. In columns 3 and 4, we estimate these regressions based on quarterly data to test the robustness of the results with regard to the interpolation of data. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	ΔCoVaR			
Frequency:	Monthly		Quarterly	
Real estate boom	0.09**	0.11***	0.15***	0.17***
	(0.031)	(0.004)	(0.001)	(0.000)
Real estate bust	0.25**	0.27**	0.42***	0.44***
	(0.036)	(0.018)	(0.000)	(0.000)
Stock boom	0.34***	0.36***	0.27***	0.29***
	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.50***	0.51***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.21***	0.20***
	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	0.00	0.00
	(0.490)	(0.492)	(0.962)	(0.963)
log(Bank size) · Real estate bust	0.17***	0.16***	0.17***	0.15***
	(0.000)	(0.000)	(0.001)	(0.002)
log(Bank size) · Stock boom	0.07***	0.06***	0.05*	0.04
	(0.002)	(0.003)	(0.090)	(0.103)
log(Bank size) · Stock bust	0.11***	0.11***	0.14***	0.14***
	(0.000)	(0.000)	(0.001)	(0.001)
Loan growth	-1.49**	-1.59**	-1.84***	-1.99***
	(0.020)	(0.014)	(0.009)	(0.005)
Loan growth · Real estate boom	1.43**	1.58**	1.72*	1.89**
	(0.044)	(0.026)	(0.071)	(0.050)
Loan growth · Real estate bust	4.47***	4.58***	4.73**	5.12***
	(0.003)	(0.002)	(0.010)	(0.005)
Loan growth · Stock boom	0.86	1.03	1.34*	1.54*
	(0.202)	(0.140)	(0.093)	(0.070)
Loan growth · Stock bust	2.81***	2.94***	3.58***	3.83***
	(0.001)	(0.001)	(0.003)	(0.001)
Leverage	0.00*	0.00	0.00*	0.00*
	(0.097)	(0.107)	(0.063)	(0.065)
Leverage · Real estate boom	0.01**	0.01**	0.01	0.01
	(0.028)	(0.020)	(0.163)	(0.131)
Leverage · Real estate bust	-0.01	-0.01	-0.01	-0.01
	(0.123)	(0.206)	(0.136)	(0.199)
Leverage · Stock boom	-0.01***	-0.01***	-0.01**	-0.01**
	(0.002)	(0.001)	(0.027)	(0.017)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.001)	(0.002)
Maturity mismatch	-0.65***	-0.62***	-0.60***	-0.58***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.26**	0.24*
	(0.024)	(0.051)	(0.042)	(0.050)
MM · Real estate bust	0.33	0.41*	0.46*	0.52*
	(0.122)	(0.063)	(0.096)	(0.078)
MM · Stock boom	0.38***	0.48***	0.41***	0.48***
	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.51**	0.60***
	(0.020)	(0.000)	(0.012)	(0.002)
Real estate boom length	-0.01		-0.01	
	(0.224)		(0.588)	
Real estate boom size		-0.00		0.01
		(0.937)		(0.608)
Real estate bust length	-0.14***		-0.15**	
	(0.000)		(0.011)	
Real estate bust size		-0.26***		-0.19
		(0.009)		(0.133)
Stock boom length	0.16***		0.11***	
	(0.000)		(0.000)	
Stock boom size		0.04***		0.02***
		(0.000)		(0.001)
Stock bust length	-0.32***		-0.20	
	(0.001)		(0.285)	
Stock bust size		-0.13		-0.04
		(0.112)		(0.766)
Bank FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	55,128	55,128
Adj. R^2	0.831	0.830	0.851	0.850
Adj. R^2 within	0.141	0.135	0.151	0.144

Table 3.C.5: The role of bank and bubble characteristics: correlated bubble episodes

Columns 1 and 2 restate our baseline regressions from Table 3.4, columns 6 and 7. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Exclude if stock market bubble in $\geq$ x% of countries	Baseline		50%		33%	
Real estate boom	0.09**	0.11***	0.09*	0.08*	0.09*	0.09*
	(0.031)	(0.004)	(0.069)	(0.060)	(0.054)	(0.053)
Real estate bust	0.25**	0.27**	0.24*	0.26**	0.27*	0.30**
	(0.036)	(0.018)	(0.062)	(0.037)	(0.060)	(0.027)
Stock boom	0.34***	0.36***	0.34***	0.33***	0.48***	0.41***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.36***	0.37***	0.30**	0.18***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.004)
log(Bank size)	0.26***	0.25***	0.30***	0.28***	0.33***	0.30***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.03	-0.03	-0.03	-0.03
	(0.490)	(0.492)	(0.130)	(0.119)	(0.149)	(0.116)
log(Bank size) · Real estate bust	0.17***	0.16***	0.17***	0.16***	0.18***	0.17***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	-0.01	-0.00	-0.05*	-0.04
	(0.002)	(0.003)	(0.889)	(0.897)	(0.059)	(0.110)
log(Bank size) · Stock bust	0.11***	0.11***	0.11***	0.11***	0.10**	0.11**
	(0.000)	(0.000)	(0.002)	(0.001)	(0.033)	(0.037)
Loan growth	-1.49**	-1.59**	-1.46**	-1.35*	-1.61**	-1.41*
	(0.020)	(0.014)	(0.038)	(0.054)	(0.029)	(0.054)
Loan growth · Real estate boom	1.43**	1.58**	1.52*	1.25	1.89**	1.39
	(0.044)	(0.026)	(0.067)	(0.116)	(0.040)	(0.113)
Loan growth · Real estate bust	4.47***	4.58***	4.95***	4.83***	5.83***	5.54***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Loan growth · Stock boom	0.86	1.03	0.94	1.01	1.81	1.62
	(0.202)	(0.140)	(0.364)	(0.337)	(0.140)	(0.179)
Loan growth · Stock bust	2.81***	2.94***	3.68***	4.13***	3.73***	4.24***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.00*	0.00	0.00	0.00	0.00	0.00
	(0.097)	(0.107)	(0.409)	(0.543)	(0.489)	(0.638)
Leverage · Real estate boom	0.01**	0.01**	0.01***	0.01***	0.01***	0.02***
	(0.028)	(0.020)	(0.006)	(0.002)	(0.007)	(0.003)
Leverage · Real estate bust	-0.01	-0.01	-0.01	-0.01	-0.01*	-0.01
	(0.123)	(0.206)	(0.147)	(0.265)	(0.096)	(0.190)
Leverage · Stock boom	-0.01***	-0.01***	0.00	0.00	0.01*	0.01**
	(0.002)	(0.001)	(0.761)	(0.704)	(0.071)	(0.039)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02**	-0.02**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.017)	(0.013)
Maturity mismatch	-0.65***	-0.62***	-0.58***	-0.52***	-0.57***	-0.50***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
MM · Real estate boom	0.21**	0.18*	0.13	0.05	0.12	0.07
	(0.024)	(0.051)	(0.239)	(0.611)	(0.313)	(0.562)
MM · Real estate bust	0.33	0.41*	0.31	0.36	0.35	0.42*
	(0.122)	(0.063)	(0.171)	(0.112)	(0.147)	(0.083)
MM · Stock boom	0.38***	0.48***	0.28**	0.31**	0.11	0.14
	(0.000)	(0.000)	(0.024)	(0.014)	(0.512)	(0.429)
MM · Stock bust	0.31**	0.43***	0.28*	0.45***	0.22	0.13
	(0.020)	(0.000)	(0.075)	(0.002)	(0.267)	(0.241)
Real estate boom length	-0.01		-0.01		-0.00	
	(0.224)		(0.267)		(0.664)	
Real estate boom size		-0.00		0.01		0.02*
		(0.937)		(0.463)		(0.089)
Real estate bust length	-0.14***		-0.16***		-0.18***	
	(0.000)		(0.000)		(0.000)	
Real estate bust size		-0.26***		-0.29***		-0.33***
		(0.009)		(0.004)		(0.001)
Stock boom length	0.16***		0.19***		0.27***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.04***		0.06***		0.07***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.32***		-0.34***		-0.25**	
	(0.001)		(0.002)		(0.013)	
Stock bust size		-0.13		-0.14		0.08
		(0.112)		(0.148)		(0.653)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	143,877	143,877	129,193	129,193
Adj. R^2	0.831	0.830	0.824	0.823	0.817	0.817
Adj. R^2 within	0.141	0.135	0.141	0.138	0.141	0.141

Table 3.C.6: The role of bank and bubble characteristics: alternative estimation of MES

Columns 1 to 4 restate the estimates from Table 3.7. Columns 5 to 8 display estimates for the same regressions, but use MES calculated based on overall market indeces instead of financial system indeces as dependent variable. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Columns 3 and 4 report regressions with all explanatory variables lagged by an additional 6 months. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	MES (financial system)				MES (Overall market index)			
Real estate boom	0.04	0.06	0.05	0.05	0.05	0.07	0.04	0.04
	(0.421)	(0.249)	(0.353)	(0.352)	(0.308)	(0.142)	(0.379)	(0.414)
Real estate bust	0.01	0.03	0.47***	0.53***	0.09	0.07	0.58***	0.56***
	(0.910)	(0.757)	(0.000)	(0.000)	(0.332)	(0.405)	(0.000)	(0.000)
Stock boom	0.10*	0.11*	0.16**	0.16**	0.11**	0.12**	0.14**	0.14**
	(0.078)	(0.062)	(0.017)	(0.021)	(0.038)	(0.025)	(0.029)	(0.029)
Stock bust	0.25***	0.25***	0.21***	0.21***	0.15***	0.15***	0.09*	0.10*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.006)	(0.093)	(0.087)
L.log(Bank size)	0.66***	0.66***	0.76***	0.74***	0.57***	0.57***	0.68***	0.66***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.20***	-0.20***	-0.17***	-0.17***	-0.19***	-0.19***	-0.16***	-0.16***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate bust	-0.01	-0.04	0.14**	0.11*	0.00	-0.01	0.13**	0.09*
	(0.814)	(0.458)	(0.011)	(0.072)	(0.972)	(0.753)	(0.011)	(0.065)
log(Bank size) · Stock boom	-0.00	-0.01	0.06*	0.06*	0.04	0.03	0.07***	0.08***
	(0.923)	(0.820)	(0.066)	(0.054)	(0.208)	(0.276)	(0.007)	(0.006)
log(Bank size) · Stock bust	0.09***	0.09***	0.12***	0.12***	0.01	0.01	0.05*	0.05*
	(0.004)	(0.004)	(0.000)	(0.000)	(0.601)	(0.581)	(0.062)	(0.051)
L.Loan growth	-6.08***	-6.07***	-3.10*	-3.15*	-6.56***	-6.53***	-4.18**	-4.23**
	(0.000)	(0.000)	(0.078)	(0.071)	(0.000)	(0.000)	(0.015)	(0.013)
Loan growth · Real estate boom	2.02	2.09	0.35	0.37	1.95	1.93	0.87	0.83
	(0.255)	(0.237)	(0.848)	(0.842)	(0.269)	(0.270)	(0.633)	(0.648)
Loan growth · Real estate bust	2.52	2.98	2.99	4.38	2.64	2.77	3.52	4.64
	(0.418)	(0.360)	(0.370)	(0.210)	(0.395)	(0.376)	(0.290)	(0.174)
Loan growth · Stock boom	0.76	0.81	1.36	1.31	1.90	1.97	3.01*	3.00*
	(0.671)	(0.656)	(0.461)	(0.471)	(0.291)	(0.274)	(0.080)	(0.077)
Loan growth · Stock bust	3.19	3.08	2.15	2.17	2.95	2.84	2.06	2.14
	(0.208)	(0.229)	(0.351)	(0.346)	(0.241)	(0.269)	(0.397)	(0.381)
L.Leverage	-0.01**	-0.01**	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01
	(0.048)	(0.045)	(0.784)	(0.712)	(0.127)	(0.126)	(0.374)	(0.340)
Leverage · Real estate boom	0.03***	0.03***	0.02***	0.02***	0.03***	0.03***	0.02***	0.02***
	(0.000)	(0.000)	(0.005)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
Leverage · Real estate bust	0.02**	0.03***	-0.01	-0.00	0.02*	0.02**	-0.01	-0.00
	(0.015)	(0.006)	(0.467)	(0.754)	(0.055)	(0.027)	(0.451)	(0.721)
Leverage · Stock boom	0.01	0.01	0.00	0.00	0.01	0.00	0.00	-0.00
	(0.136)	(0.231)	(0.819)	(0.914)	(0.296)	(0.474)	(0.973)	(0.908)
Leverage · Stock bust	-0.03***	-0.02***	-0.02***	-0.02**	-0.02**	-0.02**	-0.01*	-0.01*
	(0.000)	(0.001)	(0.009)	(0.017)	(0.010)	(0.014)	(0.052)	(0.091)
L.Maturity mismatch	-0.86***	-0.85***	-1.10***	-1.05***	-0.63**	-0.63**	-0.91***	-0.89***
	(0.005)	(0.006)	(0.000)	(0.001)	(0.026)	(0.025)	(0.001)	(0.002)
MM · Real estate boom	0.06	-0.01	0.21	0.08	0.13	0.10	0.32	0.24
	(0.789)	(0.972)	(0.365)	(0.723)	(0.549)	(0.611)	(0.145)	(0.262)
MM · Real estate bust	0.32	0.44	1.19***	1.30***	0.42	0.53*	1.17***	1.26***
	(0.368)	(0.219)	(0.003)	(0.001)	(0.177)	(0.090)	(0.002)	(0.001)
MM · Stock boom	-1.14***	-1.05***	-1.22***	-1.23***	-0.92***	-0.83***	-1.03***	-1.05***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Stock bust	-0.73***	-0.60**	-0.84***	-0.73***	-0.83***	-0.71***	-0.96***	-0.87***
	(0.007)	(0.022)	(0.001)	(0.003)	(0.002)	(0.007)	(0.000)	(0.000)
Real estate boom length	-0.02		-0.02		0.01		0.00	
	(0.131)		(0.110)		(0.512)		(0.931)	
Real estate boom size		-0.01		0.00		0.01		0.02
		(0.328)		(0.873)		(0.303)		(0.129)
Real estate bust length	-0.24***		-0.33***		-0.21***		-0.30***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Real estate bust size		-0.33***		-0.22**		-0.35***		-0.22*
		(0.000)		(0.040)		(0.000)		(0.061)
Stock boom length	0.23***		0.13***		0.23***		0.14***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Stock boom size		0.06***		0.04***		0.06***		0.04***
		(0.000)		(0.000)		(0.000)		(0.000)
Stock bust length	-0.41***		-0.30***		-0.47***		-0.31***	
	(0.000)		(0.000)		(0.000)		(0.000)	
Stock bust size		-0.22***		-0.15***		-0.26***		-0.15***
		(0.000)		(0.006)		(0.000)		(0.004)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	162,092	162,092	160,980	160,980	161,729	161,729	160,620	160,620
Adj. R^2	0.472	0.470	0.454	0.452	0.467	0.466	0.446	0.444
Adj. R^2 within	0.218	0.216	0.194	0.191	0.228	0.226	0.200	0.198

Table 3.C.7: The share of non-interest rate income

Columns 1 and 2 restate the baseline regressions from Table 3.4, columns 3 and 4. Columns 3 to 6 consider the share of non-interest rate income in various specifications. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			ΔCoVaR			
Real estate boom	0.09**	0.11***	0.20***	0.15***	0.08**	0.11***
	(0.031)	(0.004)	(0.000)	(0.000)	(0.037)	(0.005)
Real estate bust	0.25**	0.27**	0.45***	0.27**	0.25**	0.27**
	(0.036)	(0.018)	(0.000)	(0.020)	(0.038)	(0.020)
Stock boom	0.34***	0.36***	0.30***	0.38***	0.34***	0.36***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.34***	0.36***	0.38***	0.37***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***		0.26***	0.26***	0.25***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01		-0.01	-0.01	-0.01
	(0.490)	(0.492)		(0.564)	(0.522)	(0.525)
log(Bank size) · Real estate bust	0.17***	0.16***		0.14***	0.17***	0.16***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***		0.05**	0.07***	0.06***
	(0.002)	(0.003)		(0.016)	(0.001)	(0.002)
log(Bank size) · Stock bust	0.11***	0.11***		0.11***	0.11***	0.11***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**		-2.29***	-1.50**	-1.59**
	(0.020)	(0.014)		(0.001)	(0.022)	(0.016)
Loan growth · Real estate boom	1.43**	1.58**		2.50***	1.42*	1.56**
	(0.044)	(0.026)		(0.001)	(0.051)	(0.031)
Loan growth · Real estate bust	4.47***	4.58***		6.29***	4.50***	4.66***
	(0.003)	(0.002)		(0.000)	(0.003)	(0.002)
Loan growth · Stock boom	0.86	1.03		1.88**	0.91	1.05
	(0.202)	(0.140)		(0.011)	(0.175)	(0.130)
Loan growth · Stock bust	2.81***	2.94***		3.40***	2.64***	2.75***
	(0.001)	(0.001)		(0.001)	(0.002)	(0.002)
Leverage	0.00*	0.00		0.00*	0.00*	0.00
	(0.097)	(0.107)		(0.063)	(0.100)	(0.109)
Leverage · Real estate boom	0.01**	0.01**		0.01**	0.01**	0.01**
	(0.028)	(0.020)		(0.018)	(0.024)	(0.018)
Leverage · Real estate bust	-0.01	-0.01		-0.01	-0.01	-0.01
	(0.123)	(0.206)		(0.250)	(0.121)	(0.203)
Leverage · Stock boom	-0.01***	-0.01***		-0.01***	-0.01***	-0.01***
	(0.002)	(0.001)		(0.001)	(0.002)	(0.001)
Leverage · Stock bust	-0.02***	-0.02***		-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)

(*table continued on next page*)

Table 3.C.7 - *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:				ΔCoVaR		
Maturity mismatch	-0.65***	-0.62***		-0.71***	-0.70***	-0.67***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*		0.31***	0.25**	0.22**
	(0.024)	(0.051)		(0.003)	(0.018)	(0.033)
MM · Real estate bust	0.33	0.41*		0.39*	0.33	0.40*
	(0.122)	(0.063)		(0.096)	(0.147)	(0.081)
MM · Stock boom	0.38***	0.48***		0.72***	0.42***	0.54***
	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***		0.45***	0.36**	0.50***
	(0.020)	(0.000)		(0.001)	(0.019)	(0.000)
Non-interest income share			0.00	-0.00	0.00	0.00
			(0.253)	(0.989)	(0.737)	(0.856)
Non-interest income share · Real estate boom			-0.00	0.00	0.00	0.00
			(0.255)	(0.383)	(0.697)	(0.549)
Non-interest income share · Real estate bust			0.01	0.00	0.00	0.00
			(0.574)	(0.999)	(0.745)	(0.971)
Non-interest income share · Stock boom			-0.01	0.01	0.00	0.01
			(0.307)	(0.204)	(0.540)	(0.310)
Non-interest income share · Stock bust			0.01	0.00	0.00	0.01
			(0.159)	(0.240)	(0.335)	(0.159)
Real estate boom length	-0.01				-0.01	
	(0.224)				(0.228)	
Real estate boom size		-0.00				-0.00
		(0.937)				(0.926)
Real estate bust length	-0.14***				-0.15***	
	(0.000)				(0.000)	
Real estate bust size		-0.26***				-0.26***
		(0.009)				(0.009)
Stock boom length	0.16***				0.16***	
	(0.000)				(0.000)	
Stock boom size		0.04***				0.04***
		(0.000)				(0.000)
Stock bust length	-0.32***				-0.32***	
	(0.001)				(0.001)	
Stock bust size		-0.13				-0.13
		(0.112)				(0.111)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	164,840	164,840	164,840	164,840
Adj. R^2	0.831	0.830	0.819	0.827	0.831	0.830
Adj. R^2 within	0.141	0.135	0.082	0.124	0.141	0.135

Table 3.C.8: The role of bank and bubble characteristics: lead-lag structures

Columns 1 and 2 restate our baseline regressions from Table 3.4, columns 6 and 7. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and time levels. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ΔCoVaR					
Explanatory variables additionally lagged by	0 months		3 months		6 months	
Real estate boom	0.09**	0.11***	0.08***	0.08***	0.15***	0.15***
	(0.031)	(0.004)	(0.006)	(0.005)	(0.000)	(0.000)
Real estate bust	0.25**	0.27**	0.55***	0.55***	0.66***	0.67***
	(0.036)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)
Stock boom	0.34***	0.36***	0.37***	0.38***	0.39***	0.39***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.37***	0.38***	0.30***	0.31***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.26***	0.24***	0.23***	0.21***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Real estate boom	-0.01	-0.01	0.01	0.01	0.03**	0.02*
	(0.490)	(0.492)	(0.377)	(0.353)	(0.045)	(0.062)
log(Bank size) · Real estate bust	0.17***	0.16***	0.25***	0.23***	0.25***	0.24***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.09***	0.09***	0.11***	0.11***
	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock bust	0.11***	0.11***	0.13***	0.13***	0.08***	0.09***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.004)
Loan growth	-1.49**	-1.59**	-1.16**	-1.33**	-0.84	-0.95
	(0.020)	(0.014)	(0.048)	(0.019)	(0.185)	(0.122)
Loan growth · Real estate boom	1.43**	1.58**	1.46**	1.55**	1.30*	1.24*
	(0.044)	(0.026)	(0.028)	(0.020)	(0.052)	(0.060)
Loan growth · Real estate bust	4.47***	4.58***	3.20	4.13**	3.97**	4.52**
	(0.003)	(0.002)	(0.117)	(0.037)	(0.047)	(0.027)
Loan growth · Stock boom	0.86	1.03	1.29*	1.40*	1.92**	1.95**
	(0.202)	(0.140)	(0.089)	(0.060)	(0.023)	(0.019)
Loan growth · Stock bust	2.81***	2.94***	2.68***	2.48***	3.03***	2.98***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Leverage	0.00*	0.00	0.00**	0.00*	0.01**	0.00**
	(0.097)	(0.107)	(0.044)	(0.051)	(0.026)	(0.030)
Leverage · Real estate boom	0.01**	0.01**	0.00	0.01	0.00	0.00
	(0.028)	(0.020)	(0.164)	(0.110)	(0.372)	(0.345)
Leverage · Real estate bust	-0.01	-0.01	-0.02***	-0.02***	-0.03***	-0.03***
	(0.123)	(0.206)	(0.001)	(0.003)	(0.001)	(0.001)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.01***	-0.01**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.010)	(0.013)
Maturity mismatch	-0.65***	-0.62***	-0.57***	-0.54***	-0.52***	-0.49***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.11	0.06	0.13	0.11
	(0.024)	(0.051)	(0.260)	(0.538)	(0.172)	(0.246)
MM · Real estate bust	0.33	0.41*	0.67**	0.72**	0.77**	0.81***
	(0.122)	(0.063)	(0.019)	(0.013)	(0.010)	(0.008)
MM · Stock boom	0.38***	0.48***	0.36***	0.41***	0.41***	0.44***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
MM · Stock bust	0.31**	0.43***	0.38***	0.48***	0.34***	0.47***
	(0.020)	(0.000)	(0.002)	(0.000)	(0.006)	(0.000)
Real estate boom length	-0.01		-0.00		0.01*	
	(0.224)		(0.911)		(0.087)	
Real estate boom size		-0.00		0.02**		0.04***
		(0.937)		(0.026)		(0.002)
Real estate bust length	-0.14***		-0.18***		-0.19***	
	(0.000)		(0.000)		(0.000)	
Real estate bust size		-0.26***		-0.09		-0.17**
		(0.009)		(0.378)		(0.010)
Stock boom length	0.16***		0.15***		0.11***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.04***		0.04***		0.03***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.32***		-0.19**		-0.29***	
	(0.001)		(0.027)		(0.000)	
Stock bust size		-0.13		-0.14***		-0.17**
		(0.112)		(0.001)		(0.016)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	164,467	164,467	163,436	163,436
Adj. R^2	0.831	0.830	0.840	0.839	0.838	0.837
Adj. R^2 within	0.141	0.135	0.184	0.179	0.172	0.170

Table 3.C.9: Do systemic risk measures predict asset price bubbles?

Variable definitions are provided in Table 3.C.1. Standard errors are clustered at the bank and country-time level. ***, **, * indicate significance at the 1%, 5% and 10% level. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:		Real estate bubble				Stock market bubble		
ΔCoVaR	0.05	0.03			0.03	0.02		
	(0.189)	(0.362)			(0.222)	(0.516)		
MES			0.01	-0.01			0.02	0.00
			(0.620)	(0.662)			(0.425)	(0.990)
log(Bank size)	0.09	0.10*	0.12**	0.12**	-0.07	-0.06	-0.05	-0.05
	(0.154)	(0.095)	(0.015)	(0.016)	(0.101)	(0.160)	(0.145)	(0.159)
Loan growth	3.96	5.07	4.31	5.13	5.08*	5.83**	5.40*	5.99*
	(0.123)	(0.118)	(0.110)	(0.110)	(0.062)	(0.042)	(0.066)	(0.052)
Leverage	-0.01	-0.01	-0.01	-0.01	0.01**	0.01**	0.01*	0.01**
	(0.201)	(0.188)	(0.128)	(0.167)	(0.027)	(0.038)	(0.056)	(0.049)
Maturity mismatch	-0.35	-0.37	-0.34	-0.39	-0.43	-0.44	-0.41	-0.44
	(0.351)	(0.307)	(0.385)	(0.300)	(0.184)	(0.153)	(0.210)	(0.166)
GDP growth	-0.09	0.56	-0.13	0.24	3.86***	4.30***	3.93***	4.19***
	(0.952)	(0.674)	(0.933)	(0.873)	(0.006)	(0.004)	(0.008)	(0.008)
log(Interest rate)	-0.19***	-0.15***	-0.19***	-0.15***	0.05	0.07**	0.05	0.07**
	(0.000)	(0.003)	(0.001)	(0.002)	(0.116)	(0.016)	(0.113)	(0.017)
Inflation	7.52***	7.21***	7.79***	7.45***	-7.55***	-7.76***	-7.38***	-7.63***
	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Investment-to-GDP growth	0.33	0.38	0.34	0.38	0.12	0.15	0.12	0.15
	(0.222)	(0.200)	(0.205)	(0.189)	(0.667)	(0.616)	(0.656)	(0.610)
Banking crisis	-0.21**		-0.20*		-0.14***		-0.14***	
	(0.049)		(0.057)		(0.002)		(0.005)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	4,400	4,400	4,397	4,397	4,400	4,400	4,397	4,397
Adj. R^2	0.371	0.355	0.367	0.354	0.236	0.225	0.234	0.225
Adj. R^2 within	0.178	0.156	0.171	0.155	0.183	0.171	0.181	0.171

Table 3.C.10: Granger-causality tests

The granger causality tests follow the strategy in Dumitrescu and Hurlin (2012), who extend standard granger causality models to panel data by allowing for heterogeneous coefficients in the cross-sectional dimension. We use bootstrapping with 1,000 repetitions to compute p-values and allow for up to 36 lags to be included in the models while leaving the lag order selection to AIC, BIC, and HQIC. To be conservative, we report the lowest p-value resulting from the tests based on the three criteria. ***, **, * indicate significance at the 1%, 5% and 10% levels.
None of the tests rejects the null of a risk measure *not* granger causing one of our bubble measures. The results thus support the findings from our linear probability models. Neither ΔCoVaR nor MES granger causes real estate or stock market bubbles.

	ΔCoVaR		MES	
Underlying statistic:	Z-bar	Z-bar tilde	Z-bar	Z-bar tilde
Real estate bubble	0.51	0.52	0.18	0.18
Stock market bubble	0.44	0.45	0.57	0.58

Table 3.C.11: The role of bank and bubble characteristics: alternative clustering

Columns 3 and 4 restate our baseline regressions from Table 3.4, columns 6 and 7. Bubble estimates are based on the BSADF approach. Macro controls are a banking crisis dummy, GDP growth, interest rates, inflation, and investment-to-GDP growth. Variable definitions are provided in Table 3.C.1. Standard errors are clustered as indicated in the table. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ΔCoVaR					
Clustering:	bank & country-time		bank & time		bank & quarter	
Real estate boom	0.09**	0.11***	0.09**	0.11***	0.09*	0.11**
	(0.018)	(0.002)	(0.031)	(0.004)	(0.078)	(0.020)
Real estate bust	0.25**	0.27**	0.25**	0.27**	0.25	0.27*
	(0.027)	(0.012)	(0.036)	(0.018)	(0.104)	(0.066)
Stock boom	0.34***	0.36***	0.34***	0.36***	0.34***	0.36***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock bust	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size)	0.26***	0.25***	0.26***	0.25***	0.26***	0.25***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
log(Bank size) · Real estate boom	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.454)	(0.458)	(0.490)	(0.492)	(0.642)	(0.645)
log(Bank size) · Real estate bust	0.17***	0.16***	0.17***	0.16***	0.17***	0.16***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(Bank size) · Stock boom	0.07***	0.06***	0.07***	0.06***	0.07**	0.06**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.018)	(0.023)
log(Bank size) · Stock bust	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan growth	-1.49**	-1.59**	-1.49**	-1.59**	-1.49**	-1.59**
	(0.028)	(0.020)	(0.020)	(0.014)	(0.024)	(0.017)
Loan growth · Real estate boom	1.43**	1.58**	1.43**	1.58**	1.43*	1.58*
	(0.041)	(0.024)	(0.044)	(0.026)	(0.090)	(0.058)
Loan growth · Real estate bust	4.47***	4.58***	4.47***	4.58***	4.47***	4.58***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Loan growth · Stock boom	0.86	1.03	0.86	1.03	0.86	1.03
	(0.227)	(0.164)	(0.202)	(0.140)	(0.244)	(0.181)
Loan growth · Stock bust	2.81***	2.94***	2.81***	2.94***	2.81***	2.94***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Leverage	0.00*	0.00	0.00*	0.00	0.00	0.00
	(0.099)	(0.110)	(0.097)	(0.107)	(0.127)	(0.138)
Leverage · Real estate boom	0.01**	0.01**	0.01**	0.01**	0.01*	0.01*
	(0.020)	(0.014)	(0.028)	(0.020)	(0.080)	(0.067)
Leverage · Real estate bust	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.130)	(0.216)	(0.123)	(0.206)	(0.200)	(0.295)
Leverage · Stock boom	-0.01***	-0.01***	-0.01***	-0.01***	-0.01**	-0.01***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.013)	(0.006)
Leverage · Stock bust	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity mismatch	-0.65***	-0.62***	-0.65***	-0.62***	-0.65***	-0.62***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MM · Real estate boom	0.21**	0.18*	0.21**	0.18*	0.21**	0.18*
	(0.025)	(0.056)	(0.024)	(0.051)	(0.044)	(0.083)
MM · Real estate bust	0.33	0.41*	0.33	0.41*	0.33	0.41*
	(0.110)	(0.059)	(0.122)	(0.063)	(0.159)	(0.088)
MM · Stock boom	0.38***	0.48***	0.38***	0.48***	0.38***	0.48***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
MM · Stock bust	0.31**	0.43***	0.31**	0.43***	0.31*	0.43***
	(0.030)	(0.001)	(0.020)	(0.000)	(0.050)	(0.004)
Real estate boom length	-0.01		-0.01		-0.01	
	(0.183)		(0.224)		(0.293)	
Real estate boom size		-0.00		-0.00		-0.00
		(0.929)		(0.937)		(0.948)
Real estate bust length	-0.14***		-0.14***		-0.14***	
	(0.000)		(0.000)		(0.006)	
Real estate bust size		-0.26***		-0.26***		-0.26**
		(0.001)		(0.009)		(0.050)
Stock boom length	0.16***		0.16***		0.16***	
	(0.000)		(0.000)		(0.000)	
Stock boom size		0.04***		0.04***		0.04***
		(0.000)		(0.000)		(0.000)
Stock bust length	-0.32***		-0.32***		-0.32**	
	(0.001)		(0.001)		(0.013)	
Stock bust size		-0.13*		-0.13		-0.13
		(0.093)		(0.112)		(0.199)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	165,149	165,149	165,149	165,149	165,149	165,149
Adj. R^2	0.831	0.830	0.831	0.830	0.831	0.830
Adj. R^2 within	0.141	0.135	0.141	0.135	0.141	0.135

Table 3.C.12: Predicting financial crises at country level

The displayed regressions predict the occurrence of banking crises (columns 1 and 2) and financial crises (columns 3 and 4) based on the country-time specific median of ΔCoVaR and the spread between its maximum and its median. *Banking crisis* relies on an updated version of the data from Laeven and Valencia (2012). *Financial crisis* is defined as any episode of negative GDP growth that coincides with a banking crisis and is similar in spirit to the defition in Jordà, Schularick, and Taylor (2015a). *Macro controls* are comprised of credit-to-GDP growth and, in column (2), GDP growth. All explanatory variables are lagged by one month. The results are virtually identical when applying more pronounced lead-lag structures or using MES instead of ΔCoVaR. Standard errors are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels. P-values are in parentheses.

	(1)	(2)	(3)	(4)
Dependent variable:	Banking crisis		Financial crisis	
Δ CoVaR	0.01**	0.00	0.07***	0.07***
	(0.013)	(0.525)	(0.000)	(0.000)
Δ CoVaR spread	0.04***	0.04***	0.02***	0.02***
	(0.000)	(0.000)	(0.000)	(0.000)
Macro controls	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
No. of obs.	5,977	5,977	5,977	5,977
Adj. R^2	0.781	0.795	0.356	0.357
Adj. R^2 within	0.018	0.084	0.026	0.028

Table 3.C.13: Correlation between the business cycle indicator and bubble indicators

The business cycle indicator equals 1 during the boom phase of the business cycle and 0 otherwise. If business cycles moved in line with financial cycles we would thus see a positive (negative) correlation between the business cycle indicator and the bubble boom (bust) indicators. Hence, business cycles and financial cycles do not significantly co-move in our sample.

	Real estate boom	Real estate bust	Stock market boom	Stock market bust
Business cycle boom	-0.14	0.16	-0.21	0.27

Chapter 4

Macroprudential Regulation and Systemic Risk*

Abstract: Macroprudential regulation can help to control macroeconomic developments that are related to financial crises, such as credit and house price growth. However, regulatory arbitrage and the regulation-induced shifting of risks may also spur financial fragility. This paper assesses the overall consequences of macroprudential regulation for financial stability by estimating its effect on systemic risk. I find that macroprudential regulation reduces systemic risk, especially in developed, financially interconnected countries. From a cross-country perspective, macroprudential regulation at home and abroad complement each other: tighter regulation in a home country reduces its systemic risk exposure to other countries, especially when regulation abroad is strict. Macroprudential regulation abroad also reduces home countries' systemic risk exposure, but to a lesser extent. The results reveal that macroprudential regulation benefits financial stability and call for supranational coordination.

4.1 Introduction

Since the global financial crisis, policy makers have introduced a toolbox of macroprudential measures to add a systemic perspective to financial regulation. Whereas researchers and policy makers agree on the need for such a perspective, the effectiveness of macroprudential regulation remains unclear. On the one hand, macroprudential tools generally have desired effects on the variables that they directly target such as credit and house price

*This chapter is based on a single-authored working paper. I thank Tobias Berg, Martin Brown, Ralph De Haas, Luc Laeven, Yueran Ma, Martin Oehmke, Farzad Saidi, Isabel Schnabel, Sascha Steffen, as well as participants of the Finance Seminar in Bonn, the 3^{rd} CRC TR224 Conference in Mainz, and the Finance Lunch Seminar in Bonn for valuable comments and suggestions. Financial support from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (Projects C03 and C04) and through EXC 2126/1-390838866 under Germany's Excellence Strategy is gratefully acknowledged.

growth (Jiménez et al., 2017; Richter, Schularick, and Shim, 2019). On the other hand, macroprudential regulation generates market frictions and regulatory arbitrage (Aiyar, Calomiris, and Wieladek, 2014; Jiménez et al., 2017), which limits its effectiveness and shifts risks, potentially to places where they are more harmful, such as market participants which are less regulated, more systemic, or have a lower risk-bearing capacity. Overall, macroprudential regulation may thus spur financial fragility if regulatory leakage and the shifting of risks outweigh its benefits. While a great deal can be learned about channels and partial effects from the previous literature, little is known about the overall consequences of macroprudential regulation for systemic financial stability.

This paper fills this gap by empirically analyzing the relationship between macroprudential regulation and systemic risk. To this end, the analysis makes use of explicit measures of systemic risk and covers a wide array of macroprudential tools in more than 70 countries over a time horizon of 14 years. This broad sample also allows to asses which types of tools achieve most for financial stability and under what circumstances. Additionally, the paper takes a cross-country perspective and analyzes cross-border spillovers of macroprudential regulation and the complementarity between macroprudential regulation at home and abroad.

Assessing the overall effect of macroprudential regulation on financial stability is particularly important as the regulation has direct costs for the real economy (Richter, Schularick, and Shim, 2019), whereas its potential benefits, such as an avoided financial crisis, may take years to come and are not easily observable (Forbes, 2019). This combination of knowledge about costs and uncertainty about benefits makes it difficult to defend the application of macroprudential tools. In light with this observation, politicians appear hesitant to tighten macroprudential regulation (Müller, 2019). Therefore, it is important to better understand the effectiveness of macroprudential regulation in fostering financial stability.

In this context, focusing on systemic risk as an outcome of macroprudential regulation has several advantages. First, unlike more intermediate variables, it facilitates estimating an overall relationship between macroprudential regulation and financial stability. It simultaneously allows for effects through different channels, thereby accounting for desired effects as well as regulatory leakage and the shifting of risks due to regulatory arbitrage. Second, compared to a binary variable indicating financial crises, systemic risk measures have several statistical and conceptual advantages that are relevant when analyzing macroprudential regulation. Systemic risk measures are continuous and, hence, more informative than a financial crisis indicator variable. This is especially important for the analysis, because financial crises are rare events and the time that has passed since the widespread use of macroprudential tools is limited. The continuous nature also allows to capture the timing of systemic financial distress more accurately. For instance, many financial crises occur after the burst of asset price bubbles, but systemic risk increases already during their emergence (Brunnermeier, Rother, and Schnabel, 2020). Similarly, (countercyclical) macroprudential tools may affect systemic risk already well before a financial crisis. Lastly, systemic risk measures also account for financial fragility outside of financial crises. They can thus assess macroprudential regulation even if a financial crisis occurs only after the end of the sample.[1]

To measure systemic risk, this paper employs the marginal expected shortfall (MES) proposed by Acharya et al. (2017) and, for robustness, the conditional value at risk (ΔCoVaR) introduced by Adrian and Brunnermeier (2016). Both measures are estimated based on tail correlations of equity returns but take complementary perspectives. MES measures the return loss of an entity conditional on a financial system experiencing distress. ΔCoVaR estimates the additional value at risk in the financial system associated with an entity experiencing distress. Hence, MES treats the entity as risk recipient while ΔCoVaR treats it as risk contributor. I complement these risk measures with the data set on macroprudential regulation introduced by Cerutti, Claessens, and Laeven (2017). It includes bankbased, borrowerbased, countercyclical, and cross-sectional tools and provides the precise timing of their use. For the analyses in this paper, tools are oftentimes aggregated into an index that captures the overall tightness of macroprudential regulation.

The results show that tightening macroprudential regulation in a country is associated with a significant decrease in overall systemic risk in this country. Specifically, a standard-deviation increase in the macroprudential index is associated with a decrease of country-level systemic risk by 0.43 standard deviations. During the global financial crisis, which saw an unprecedented surge in systemic risk, MES increased by more than 1.5 standard deviations in the United States. This comparison suggests that macroprudential regulation

[1]Systemic risk measures are also meaningful with respect to the relationship between financial fragility and distress in the real economy, as they predict downturns in the real economy (Allen, Bali, and Tang, 2012; Engle, Jondeau, and Rockinger, 2015; Giglio, Kelly, and Pruitt, 2016; Brownlees and Engle, 2017).

can significantly decrease systemic risk, but it may be insufficient to counteract particularly outstanding increases in financial fragility.

When looking at individual tools, systemic risk does not significantly increase after the introduction of any tool, but some types of tools appear to be more effective than others. The decreases of systemic risk are associated with a tightening of bank-based macroprudential tools rather than their borrower-based counterparts. The distinction between countercyclical and cross-sectional tools does not reveal such coherent differences. Moreover, I find no evidence of a nonlinear relationship between macroprudential regulation and systemic risk or a complementary character of (groups of) instruments within a country.

The effectiveness of macroprudential regulation also differs across country characteristics. After a tightening of regulation, systemic risk decreases significantly more in developed than in developing countries.[2] Whereas there are no significant heterogeneities across the interconnectedness of the real economy, systemic risk also decreases more in countries with a higher degree of de jure financial openness, pointing toward a relevance of the financial interconnectedness across country borders.

This relevance of financial interconnectedness also becomes apparent when analyzing cross-country systemic risk. On average, the systemic risk exposure of a home country to a foreign country's financial system does not decrease in the home country's macroprudential regulation unless the home and foreign countries are located within the same region or bilateral cross-border claims are sufficiently large. In line with expectations, also the *level* of the cross-country systemic risk exposure is significantly larger when bilateral claims are large. Hence, macroprudential regulation in a home country can strengthen the resilience of the financial system to cross-border systemic risk if these risks are large in the first place due to heavily interconnected financial systems. Moreover, in line with the within-country results, developed countries' systemic risk exposures decreases more in macroprudential regulation than those of developing countries. Overall, macroprudential regulation in a home country thus can but does not always reduce its systemic risk exposure to foreign financial systems.

[2] This finding may be explained by developing countries experiencing capital inflows after a tightening of regulation, which bring the risk of sudden stops and reversals (cf. Norring (2019)).

As regards regulation in the foreign country, there is generally no significant relationship with the home country's systemic risk exposure unless the financial systems are sufficiently interconnected. Given interconnectedness, the decrease of systemic risk is smaller compared to the decrease which is related to tighter regulation in the home country. Taken together, these results on cross-country systemic risk exposures indicate that regulation in one country can strengthen its financial system's resilience without having negative spillovers on other countries' financial stability. Hence, the additional stability in the regulated country's financial system and the, thereby, smaller spillover risks to other countries appear to outweigh the destabilizing effects of any cross-border shifting of risks due to regulatory arbitrage.

Lastly, the results reveal a complementarity between macroprudential regulation at home and abroad. A tightening of macroprudential regulation in a home country reduces its cross-border systemic risk exposure more if macroprudential regulation abroad is tighter. Hence, the regulation is particularly effective when opportunities for regulatory arbitrage are limited.

For identification, the baseline regressions control for a broad array of macroeconomic developments such as credit-to-GDP growth, monetary policy, banking crises, and real GDP growth. Additionally, the within-country setting employs country and region-time fixed effects. The regressions of cross-country systemic risk exposures mostly include home country-foreign country, home country-time, and foreign country-time fixed effects. The main challenge for identification, mostly in the within-country setting, results from the fact that regulation oftentimes gets introduced as a response to financial fragility. To address this reversed causality concern, I employ two instrumental-variable approaches based on a political-economy argument. Politicians appear hesitant to employ macroprudential tools in fear of antagonizing voters who may suffer negative consequences of a tighter regulation such as difficulties to obtain loans. Whether politicians have a direct say in the introduction of macroprudential tools varies across countries and tools. Following the idea in Gadatsch, Mann, and Schnabel (2018), the analysis exploits this heterogeneity by using the share of tools over which politicians have no direct control as an instrument for macroprudential regulation. Moreover, the use of macroprudential regulation varies with the electoral cycle (Müller, 2019). I exploit a measure based on the time until the next major election as a second instrument. The first-stage regressions show that macroprudential policy is indeed tighter if politicians have less direct control over macroprudential tools and if there is more time until the next election. The second-stage estimates support the baseline findings.

The results suggest several policy implications. First, from a financial-stability perspective, negative partial effects of macroprudential regulation should not keep regulators from using the macroprudential toolbox. The results show that macroprudential regulation reduces systemic risk, indicating that the regulation's benefits for financial stability outweigh the negative effects through regulatory arbitrage and the shifting of risks. Hence, these negative effects can serve as a motivation to design regulation to limit arbitrage opportunities, but they cannot serve as an argument against macroprudential regulation itself. Second, coordinating macroprudential regulation on a supranational level can increase the effectiveness of the regulation. A tighter regulation in one country does not increase foreign countries' systemic risk exposures, but regulation at home and abroad are complements. Hence, macroprudential regulation reduces systemic risk also in the absence of coordination, but a coordinated use of regulation across countries is more effective. Third, the benefits of macroprudential regulation are highly heterogeneous. The decrease in systemic risk after a tightening of macroprudential regulation differs greatly across types of tools and country characteristics. While welfare implications are beyond the scope of this analysis, these heterogeneous effects can be informative with respect to the cost-benefit trade-off that is inherent to the decision about the use of macroprudential regulation. Lastly, the use of macroprudential tools varies with the institutional framework. Macroprudential tools are more frequently applied if politicians have no direct control over their application and if there is more time until the next election. Such potential hurdles to a timely application of macroprudential tools may have to be taken into account for the design of the institutional framework of macroprudential regulation.

4.2 Contribution to the literature

The paper contributes to the literature in macroeconomics and finance that studies macroprudential regulation and financial stability. During the recent years, the literature has seen a surge in contributions on macroprudential regulation. Galati and Moessner (2018) and Forbes (2019) take stock of this literature. Part of the empirical literature indicates that macroprudential regulation has desired effects. Loan-to-value ratios reduce aggregate credit growth and house prices (Richter, Schularick, and Shim, 2019). House price growth can also be limited using capital requirements, marginal reserve requirements (Vandenbussche, Vogel, and Detragiache, 2015), and loan-to-value ratios (Ahuja and Nabar, 2011; Wong et al., 2011). Claessens, Ghosh, and Mihet (2013) find that both borrower-targeted and bank-targeted macroprudential measures reduce the build up of imbalances during booms. Gadatsch, Mann, and Schnabel (2018) emphasize the role of borrower-based measures in reducing credit growth. Altunbas, Binici, and Gambacorta (2018) find that macroprudential regulation reduces idiosyncratic bank risk. Whereas Ostry et al. (2012) show that capital controls and prudential measures can counteract the risks associated with large capital inflows, Forbes (2020) finds only limited evidence for favorable effects of macroprudential regulation on surges of capital flows and sudden stops.[3][4]

However, the literature also exposes channels that are detrimental to the stabilizing effects of macroprudential regulation. For instance, the effectiveness of macroprudential regulation can be limited if it lacks coordination on a supranational level. In Aiyar, Calomiris, and Wieladek (2014), one third of the effect from tightening capital regulation on credit growth is offset by foreign branches increasing lending. Similar in spirit, Avdjiev et al. (2017) find that a tightening of macroprudential regulation reduces credit growth of domestic banks but increases cross-border lending. Cross-border spillover effects of macroprudential regulation on credit growth are heterogeneous across tools and banks (Buch and Goldberg, 2017), and increase in the degree of financial market integration (Franch, Nocciola, and Żochowski, 2019). Whereas these channels are associated with regulatory arbitrage across jurisdictions, the effectiveness of regulation can also be in question due to regulatory arbitrage by banks for which the regulation is less binding (Jiménez et al., 2017; Basten, 2020) or banks for which the regulation is binding only for certain parts of their business (Acharya

[3]When it comes to addressing imbalances in the financial sector, macroprudential policy provides additional value over monetary policy, especially if monetary policy is constrained by the zero lower bound (Korinek and Simsek, 2016) or fixed exchange rates (Farhi and Werning, 2016). Further studies of the interactions between macroprudential and monetary policy include Monnet and Vari (2019), Takáts and Temesvary (2019), and Adrian et al. (2020).

[4]van Bekkum et al. (2019) analyze household reactions to the introduction of mortgage LTV ratios.

et al., 2020). Leakage can also occur through firm behavior (Ahnert et al., 2021). Furthermore, Müller (2019) demonstrates how the use of macroprudential instruments varies with the political cycle so that the effectiveness of macroprudential regulation may suffer from a lack of political independence.[5] Krug, Lengnick, and Wohltmann (2015) argue that the effectiveness of macroprudential regulation is limited, especially compared to its complexity. It can also face time-inconsistency problems (Bianchi and Mendoza, 2020), questioning the stabilizing effect. Overall, it appears unclear how much financial regulation has achieved since the global financial crisis.[6]

While the benefits from macroprudential regulation remain unclear, the regulation has direct costs. For instance, not all credit booms are bad (Gorton and Ordoñez, 2019), so that macroprudential policy needs to weight the benefits from stopping unhealthy credit booms with the risk of neutralizing good ones (Gertler, Kiyotaki, and Prestipino, 2020). Richter, Schularick, and Shim (2019) provide empirical evidence that loan-to-value ratios reduce aggregate real GDP growth. More generally, there appears to be a trade-off between long-run GDP growth and financial stability (Bianchi and Mendoza, 2020). Moreover, economic slowdowns feed back into the financial system and if these slowdowns are large enough, they may ultimately even increase financial fragility (Forbes, 2019). In light of these costs of macroprudential regulation, it is particularly important to know the benefits of macroprudential regulation for financial stability.

This paper contributes to the literature on macroprudential regulation by analyzing the effect of macroprudential regulation on systemic risk. Unlike the previous literature, the focus on systemic risk allows to directly quantify effects on systemic financial stability rather than on intermediate variables such as credit growth or house prices. This setup also allows to estimate equilibrium effects that simultaneously consider both the stabilizing and destabilizing channels revealed by the previous literature. The study thus provides an assessment of the bottom-line benefits of macroprudential regulation for financial stability.

The paper also closely relates to the literature on systemic risk. Whereas the notion of systemic risk existed already before the global financial crisis (de Bandt and Hartmann,

[5] Aikman et al. (2019a) estimates further determinants of the use of macroprudential tools.

[6] For a discussion of whether present-day macroprudential regulation could have reduced the fallout during the global financial crisis, see Martin and Philippon (2017) and Aikman et al. (2019b).

2000), numerous contributions on this topic have emerged in its aftermath. Allen, Babus, and Carletti (2012) and Brunnermeier and Oehmke (2013) provide comprehensive reviews including the theoretical literature. Numerous studies introduce measurement approaches to systemic risk. Bisias et al. (2012) provide an overview of approaches and categorize these. Particularly prominent contributions include Acharya, Engle, and Richardson (2012), Adrian and Brunnermeier (2016), Brownlees and Engle (2017), and Acharya et al. (2017). Related to the topic of macroprudential regulation, Gauthier, Lehar, and Souissi (2012) use several systemic risk measures to assign hypothetical capital surcharges to financial institutions, finding that the resulting allocations of capital would increase financial stability. This paper builds on established measures of systemic risk and contributes to the literature by analyzing the actually used macroprudential regulation as an important driver of systemic risk and its measures.

4.3 Data and empirical model

The analyses in this paper are based on a broad sample that contains yearly information on systemic risk and the use of 12 macroprudential tools in 73 countries between 2000 and 2014.[7] This section elaborates on the data, its sources, and the two main empirical models. Table 4.A.1 in the Appendix defines the variables and summarizes the data sources.

4.3.1 Data

4.3.1.0.1 Macroprudential regulation The information on macroprudential regulation draws upon the data set introduced in Cerutti, Claessens, and Laeven (2017). It covers 12 macroprudential tools and precisely reflects at what time each tool has been activated or deactivated. The tools are countercyclical capital buffers, countercyclical loan-loss provisions, debt-to-income ratios, loan-to-value ratios, limits on domestic-currency loans, limits on foreign-currency loans, concentration limits, limits on interbank exposures, leverage ratios, reserve requirements, tax on financial institutions, and capital surcharges on systemically important financial institutions. To obtain a measure of the overall macroprudential stance, I follow

[7]The sample contains all countries with data on macroprudential regulation and sufficient equity return observations for the estimation of the systemic risk measures.

Cerutti, Claessens, and Laeven (2017) and combine the data into an index that equals the number of macroprudential tools that are active at a given time in a given country.

Importantly, the term *macroprudential* has become a buzzword only after the global financial crisis, yet some parts of what is nowadays considered the macroprudential toolbox have been used already before the crisis, especially in developing countries and emerging market economies. Table 4.1 displays summary statistics for the dataset on which the analysis of systemic risk *within country* is based. The median of the macroprudential index equals 2. At most 8 tools are simultaneously active and the standard deviation of the macroprudential index equals 1.7. The variation stems from both the cross-sectional (between standard deviation: 1.6) and the time dimension (within standard deviation: 0.7). The use of various tools is significantly correlated (see Table 4.A.2), mostly positively. An average correlation of 0.1, however, suggests that most tools are used independently of each other.

4.3.1.0.2 Systemic risk The paper analyzes the relationship between macroprudential regulation and two different types of systemic risk. First, the systemic risk within one country's financial system and second, systemic risk spillovers between a home country's financial system and a foreign country's financial system. Hence, for the purpose of this analysis, the applied systemic risk measure needs to be able to quantify a systemic risk relationship between two entities. The literature offers several candidates. I make use of two particularly prominent measures, MES (Acharya et al., 2017) and ΔCoVaR (Adrian and Brunnermeier, 2016), which take complementary perspectives. MES treats banks as *risk recipients* and quantifies the systemic risk exposure of a bank to a financial system as the bank's equity losses conditional on distress in the financial system. ΔCoVaR thinks of banks as *risk contributors* and quantifies the systemic risk contribution of a bank to a financial system as the additional value at risk of a financial system conditional on the bank being distressed.

The estimation of both measures is based on tail correlations of equity returns. I obtain data on all publicly listed banks' equity returns and market values from Thomson Reuter's Eikon. Following Acharya et al. (2017), I calculate MES at bank level as the average equity return loss during the 5% days during which a financial system exhibits its highest losses during the past year:

$$MES_t^{b,system} = \frac{1}{\text{\# of days in } \mathbb{Z}_{system,t}} \sum_{\tau \in \mathbb{Z}_t^{system}} X_\tau^b \, , \tag{4.1}$$

where $\mathbb{Z}_t^{system}$ denotes the set of trading days with these 5% worst returns of the financial system in a country at time t. For the within-country analyses, the financial system is that of the bank's home country and I aggregate the data at the country time levels by taking averages across the MES of all banks in a country. For the cross-country analyses, I calculate a banks' systemic risk exposures with respect to foreign countries' financial systems and, correspondingly, aggregate the data at the home-country foreign-country time level.

Mirroring the above provided description of ΔCoVaR, the measure can formally be expressed as

$$\Delta CoVaR_q^{system|b} = CoVaR_q^{system|X^b=VaR_q^b} - CoVaR_q^{system|X^b=VaR_{50}^b} \, , \tag{4.2}$$

where X_b denotes the return loss of bank b and q refers to a percentile of the loss distribution. The VaR is implicitly defined by $Pr(X^i \leq VaR_q^i) = q\%$, and CoVaR is implicitly defined by $Pr(X^{system} \leq CoVaR_q^{system|C(X^i)} | C(X^i)) = q\%$. Following Adrian and Brunnermeier (2016), I estimate ΔCoVaR using quantile regressions. In line with the calculation of MES, the financial system again refers to either that of a bank's home country or that of a foreign country and I aggregate the data at the home-country foreign-country time level.

4.3.1.0.3 Further macroeconomic variables The data on macroprudential regulation and systemic risk is complemented by data on real GDP growth (obtained from the Worldbank), credit-to-GDP growth (Worldbank), a banking crisis indicator variable (Laeven and Valencia (2018)), monetary policy rates (Datastream, OCED, IMF, BIS), inflation (Worldbank), trade as measured by the sum of imports and exports in percent of GDP (Worldbank), a de jure measure of capital account openness (Chinn and Ito (2006)), government debt to GDP (IMF's historical government debt database), and the exchange rate (IMF) calculated as the nominal exchange rate in units of national currency per USD · (U.S. CPI / local CPI).

In the sample, real GDP growth and credit-to-GDP growth are on average positive (1.9 and 3.6) but vary greatly (see Table 4.1). A banking crisis has on average been present during 10% of the observations. Average inflation (5.6) is high compared to current developed countries' central bank targets. Trade, financial openness, government debt to GDP, and exchange rates vary greatly across observations, thereby mirroring the diverse developments in the broad sample of 74 countries over 24 years.

Table 4.1: Descriptive statistics

The table displays statistics for the sample used to analyze the relationship between macroprudential regulation and systemic risk within a country. Table 4.A.1 provides variable definitions and data sources.

	N	Mean	Median	SD	Min	Max
MES	905	2.80	2.46	1.64	0.08	6.58
ΔCoVaR	877	6.09	5.30	3.03	1.70	20.10
Macroprudential index	905	1.9	2.0	1.7	0.0	8.0
Real GDP growth	905	3.6	3.7	3.5	-14.8	17.3
Credit-to-GDP growth	905	31.3	2.6	165.1	-100.0	994.5
Banking crisis	905	0.1	0.0	0.3	0.0	1.0
Monetary policy rate	905	5.6	4.1	5.3	0.0	49.1
Inflation	877	4.5	3.1	5.3	-4.5	54.9
Trade	905	92.8	74.1	66.6	19.8	442.6
Financial openness	899	70.2	81.9	33.5	0.0	100.0
Government debt to GDP	901	53.3	45.0	35.6	0.5	244.5
Exchange rate	873	331.8	7.2	1,535.5	0.3	16,977.2
% non-politician	905	44.9	33.3	45.2	0.0	100.0
Election	671	0.2	0.0	0.3	0.0	1.0

4.3.2 Empirical model

4.3.2.0.1 Within-country systemic risk To analyze the relationship between macroprudential regulation and systemic risk within a country, the baseline model regresses systemic risk (measured by MES or ΔCoVaR) in country c at year t on the index of macroprudential regulation, country and region-time fixed effects (α_c and $\alpha_{r,t}$), and macroeconomic control variables.

$$\begin{aligned} Systemic\ risk_{c,t} &= \beta_1 \cdot Macroprudential\ regulation_{c,t-1} \\ &\quad + \gamma \cdot Macroeconomic\ controls_{c,t-1} + \alpha_c + \alpha_{r,t} + u_{c,t} \end{aligned} \tag{4.3}$$

All explanatory variables enter the regressions lagged by one year. To include region-time fixed effects, I group countries into regions based on their geographical location.[8] Control

[8] The regions are Africa, Asia, Europe, Middle East, North America, Oceania, and South America.

variables include real GDP growth, credit-to-GDP growth, a banking crisis indicator, and the monetary policy rate, as recessions can put a strain on banks' balance sheets, credit booms are often followed by financial crises (Schularick and Taylor, 2012) during which systemic risk spikes, and monetary policy can contribute to financial fragility, for instance, when it is too lose or pricks asset price bubbles (Brunnermeier and Schnabel, 2016). In some regressions, control variables additionally account for inflation, trade, financial openness, government debt to GDP, and the exchange rate. This reduces the sample size due to limited data availability, but the results are robust. Standard errors are clustered at the country level to account for a correlation of error terms over time. A larger value of macroprudential regulation corresponds to tighter regulation. Hence, a negative coefficient β_1 would indicate a decrease in systemic risk after a tightening of the regulation.

The main potential concern for identification is reverse causality, as regulation is usually designed as a response to lacking financial stability. To address this concern, Section 4.4.2 introduces two instrumental-variable approaches based on a political-economy argument. More specifically, I exploit exogenous variation in politicians' ability and election-driven incentives to opt for loser macroprudential regulation to identify exogenous variation in the regulation.

4.3.2.0.2 Cross-country systemic risk exposures The baseline model of cross-country systemic risk explains the systemic risk exposure of home country h's financial system to foreign country f's financial system (measured by MES) at year t by macroprudential regulation in the home country and macroprudential regulation in the foreign country while controlling for home country-foreign country ($\alpha_{h,f}$), home-country region-time ($\alpha_{hr,t}$) and foreign-country region-time ($\alpha_{fr,t}$) fixed effects, as well as home and foreign country macroeconomic control variables.

$$\begin{aligned} Systemic\ risk_{h,f,t} &= \beta_1 \cdot Macroprudential\ regulation_{h,t-1} + \beta_2 \cdot Macroprudential\ regulation_{f,t-1} \\ &+ \gamma_1 \cdot Macroeconomic controls_{h,t-1} + \gamma_2 \cdot Macroeconomic controls_{f,t-1} \\ &+ \alpha_{h,f} + \alpha_{hr,t} + \alpha_{fr,t} + u_{h,f,t} \end{aligned} \tag{4.4}$$

In robustness checks, systemic risk is measured by ΔCoVaR instead of MES. Explanatory variables are lagged by one year. Standard errors are clustered at the home-country and foreign-country levels. Many regressions in this analysis of cross-country systemic risk also interact macroprudential regulation with variables that vary at the home-country foreign-country time level. These regressions additionally include home country-time and foreign country-time fixed effects.

4.4 Macroprudential regulation and systemic risk

4.4.1 Baseline results

This section starts the analysis of the relationship between macroprudential regulation and systemic risk by illustrating how systemic risk evolves after a change in macroprudential regulation. To this end, I estimate the baseline model (Equation 4.3), which regresses MES on lagged macroprudential regulation, the lagged control variables, and bank and region-time fixed effects.

Table 4.2 reports the results. Regardless of whether the regression includes only the fixed effects (column 1) or also the macroeconomic control variables (column 2), the coefficient of macroprudential regulation is negative and statistically significant. The same applies when including additional control variables for robustness in column 3. Hence, systemic risk decreases after macroprudential regulation has been tightened.

Table 4.A.3 reports the coefficient of control variables. In line with expectations, systemic risk is elevated during banking crises and increases in government debt to GDP. The coefficients of the other control variables are not statistically significant, which is in line with a large share of their variation being filtered out by country and region-time fixed effects.

In column 4, I add a squared term of macroprudential regulation to explore a potentially quadratic relationship between this variable and systemic risk. Such a relationship could, for instance, exist if several instruments in the macroprudential index are complements or the joint complexity of activated tools is detrimental to financial stability. In these cases, systemic risk would decrease less after the activation of an additional macroprudential tool if more tools had already been active. The estimates provide no indication of a dependence of the relationship between macroprudential regulation and systemic risk on the level of the macroprudential index as the coefficient of the squared term is not significantly different from zero. A binned scatter plot of MES and the macroprudential index (see Figure 4.A.1) does not indicate a no non-linear relationship either. Overall, the results in this section illustrate that systemic risk decreases after macroprudential regulation has tightened.

Table 4.2: Macroprudential regulation and systemic risk

Macro controls are GDP growth, credit-to-GDP growth, a banking crisis indicator variable, and the monetary policy rate. Additional *macro controls* account for inflation, trade, financial openness, government debt to GDP, and the exchange rate. Table 4.A.3 reports the coefficient of control variables. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Macroprudential regulation	-0.205**	-0.184*	-0.133*	-0.152*
	(0.048)	(0.058)	(0.073)	(0.080)
Macroprudential regulation^2				0.008
				(0.607)
Country FE	Yes	Yes	Yes	Yes
Region-time FE	Yes	Yes	Yes	Yes
Macro controls	No	Yes	Yes	Yes
Additional macro controls	No	No	Yes	Yes
No. of obs.	905	905	861	861
Adj. R^2	0.633	0.640	0.653	0.652
Adj. R^2 within	0.017	0.034	0.051	0.050

4.4.2 Instrumental-variable approaches

To address the reverse causality concern of macroprudential regulation usually being a response to financial fragility, this section introduces two instrumental variables based on a political-economy argument: politicians can be hesitant to tighten macroprudential regulation in fear of antagonizing voters who suffer direct consequences of this tightening, such as lacking access to loans.

Based on this narrative, I follow the idea in Gadatsch, Mann, and Schnabel (2018) to exploit country and tool-specific differences in politicians' ability to affect the use of macroprudential regulation and define the first instrument as the share of macroprudential tools over which politicians have no direct control. While legislators need to construct the legal basis for macroprudential regulation, the control over the activation and deactivation of tools varies across countries and tools.[9] Importantly, this institutional arrangement is predetermined and, hence, independent of the current level of systemic risk. I proxy for politicians' control over instruments based on information from Cerutti, Claessens, and Laeven (2017) whether the decision about the use of a tool lies with a central bank or not. On average, 45% of tools are not controlled by politicians (see Table 4.1). The standard deviation of the instrumental variable equals 45.2, illustrating the large variation in institutional settings.

The second instrument exploits electoral cycles. If politicians are worried about voters' reactions, they should be particularly hesitant to tighten regulation before an election. Indeed, Müller (2019) documents that macroprudential regulation is loser before elections. Again, the exogeneity of the instrument comes from the fact that electoral cycles are predetermined and thus not driven by systemic risk. I define the instrument as the share of quarters in a year that are no further than one year from the next main election.[10] The mean of the variable equals 0.25, which corresponds to elections on average taking place every 4 years (see Table 4.1).

Table 4.3 reports the results of the instrumental-variable regressions. Column 1 includes the country and region-time effects as well as the macroeconomic control variables. The first-stage estimates show that the macroprudential index is indeed significantly higher the more instruments are out of the control of politicians and significantly lower if there is an upcoming election. The results are thus in line with the idea that politicians can be hesitant to apply macroprudential tools. The F-value of the test for joint significance of the instruments equals 10.9, rejecting the hypothesis of weak instruments at the conventional levels. Moreover, the P-value of Hansen's test of overidentifying restrictions equals 0.4, thereby providing no evidence of endogeneity of the instruments. Table 4.A.4 reports full first-stage regressions. In the second stage, the coefficient of macroprudential regulation is negative and statistically significant, thereby supporting the earlier findings of macroprudential regulation reducing systemic risk.

[9] Margerit, Magnus, and Mesnard (2017) describe the heterogeneity of institutional settings in the European Union.

[10] "Main" election referring to nationwide presidential or legislative elections, depending on the political system.

According to the estimates, the activation of one additional tool reduces MES by 0.413 percentage points. This effect is sizeable, as a standard-deviation increase in the macroprudential index reduces systemic risk by 0.43 (=1.7·0.413/1.64) standard deviations. To put the size of the estimate further into perspective, consider the global financial crisis, an unprecedented event in terms of financial fragility. During this crisis, MES increased by more than 1.5 (≈2.5/1.64) standard deviations in the United States (see Figure 4.A.2 and Table 4.1). As an alternative comparison, Brunnermeier, Rother, and Schnabel (2020) estimate that country-level systemic risk increases by approximately 0.8 standard deviations during an asset price bubble of average characteristics. The comparisons illustrate that macroprudential regulation can significantly decrease systemic risk, but it is most likely unable to fully offset larger surges in financial fragility.

Table 4.3: Instrumental-variable approach

In this table, the share of instruments not directly controlled by politicians and the electoral cycle are used as instruments for macroprudential regulation. In column 3, the elections instrumental variable is exclusively based on elections that take place at the end of the regular term. Column 4 defines the election variable as an indicator variable equal to one during election years. The bottom part of the table displays selected statistics on the first-stage regressions. Full first-stage regressions are reported in Table 4.A.4. *Macro controls* are GDP growth, credit-to-GDP growth, a banking crisis indicator variable, and the monetary policy rate. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Macroprudential regulation	-0.413**	-0.385**	-0.376**	-0.369**
	(0.047)	(0.035)	(0.039)	(0.042)
Country FE	Yes	Yes	Yes	Yes
Region-time FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Additional macro controls	No	Yes	Yes	Yes
No. of obs.	657	616	616	616
Adj. R^2	0.673	0.691	0.692	0.692
Adj. R^2 within	-0.079	-0.023	-0.022	-0.021
First-stage results				
% non-politician supervised	0.02***	0.02***	0.02***	0.02***
	(0.000)	(0.000)	(0.000)	(0.000)
Upcoming election	-0.09*	-0.11**	-0.12**	-0.17**
	(0.077)	(0.021)	(0.02)	(0.017)
F-value (joint significance)	10.9	12.4	12.3	12.1
Hansen's test of overidentifying restrictions (H0: instruments are exogenous)				
P-value	0.411	0.693	0.337	0.181

Columns 2 to 4 of Table 4.3 report additional instrumental-variable regressions to assess the robustness of the previous estimates. Specifically, column 2 adds additional macroeconomic control variables to the model. In column 3, I construct the elections instrumental variable based only on elections that take place at the end of the regular term to exclude elections that could be caused by governments falling apart due to a financial crisis. Column 4 defines the election variable as an indicator variable equal to one during election years. The results are robust in all three alternative specifications.

Overall, the results in this section support the baseline finding that systemic risk decreases after macroprudential regulation is tightened. The results also show that the size of the decrease in systemic risk is economically meaningful. Lastly, macroprudential regulation is less tight if politicians decide about the activation of macroprudential tools and close to elections, suggesting the presence of significant political frictions in the application of macroprudential tools.

4.4.3 Heterogeneities across macroprudential tools

Having established that systemic risk decreases in the macroprudential index in the previous sections, the subsequent section analyzes to what extent this relationship holds across different types of tools. For this purpose, I re-estimate the baseline regressions (Equation 4.3) but create indices that include certain types of tools instead of a single index that includes all tools.

Table 4.4 reports the results. Column 1 distinguishes between borrower- and bank-based tools.[11] The coefficient of both indices are negative, but only the one of bank-based tools is statistically significant. As the difference in the significance levels and the coefficients is comparably small, I remain conservative and interpret this result only as evidence that no group of instruments has detrimental effects on financial stability. Column 2 adds an interaction term between the borrower-based and the bank-based index to the previous specification. The results remain unchanged an the interaction term is not statistically significant. I thus find evidence of both types of macroprudential tools neither being complements nor substitutes.

[11] Borrower-based tools: loan-to-value and debt-to-income ratios; bank-based tools: countercyclical capital buffer, countercyclical loan-loss provisions, limits on domestic-currency loans, limits on foreign-currency loans, concentration limits, interbank limits, leverage ratios, reserve requirements, a tax on financial institutions, and capital surcharges on SIFIs.

Column 3 distinguishes between countercyclical and cross-sectional tools, that is, tools that attempt to manage the evolution of financial fragility such as countercyclical capital buffers or loan-loss provisions, and tools that target particularly risky banks such as systemically important financial institutions.[12] The coefficients of both indices are negative, but only countercyclical tools enter the regression significantly. Again the difference in significance levels is on the small side, but the difference in the size of coefficients is large (-0.738 vs. -0.1). In column 4, I interact both indices. Once more, the previous results are robust and I find no evidence of complements or substitutes.

Table 4.4: Heterogeneities across macroprudential tools

Borrower-based tools equals the number of borrower-based macroprudential tools that are currently used in a country. Bank-based tools, countercyclical tools, and cross-sectional tools are indices following the same logic for corresponding groups of tools. *Borrower-based tools*: loan-to-value and debt-to-income ratios. *Bank-based tools*: countercyclical capital buffer, countercyclical loan-loss provisions, limits on domestic-currency loans, limits on foreign-currency loans, concentration limits, interbank limits, leverage ratios, reserve requirements, a tax on financial institutions, and capital surcharges on SIFIs. *Countercyclical tools*: countercyclical loan-loss provisions, countercyclical capital buffers, and reserve requirements. *Cross-sectional tools*: loan-to-value ratios, debt-to-income ratios, limits on domestic-currency loans, limits on foreign-currency loans, concentration limits, interbank limits, leverage ratios, a tax on financial institutions, and capital surcharges on SIFIs. Table 4.A.5 reports results for an alternative delineation of countercyclical and cross-sectional tools. Section 4.3.1 discusses the macroprudential tools. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Borrower-based tools	-0.158	-0.169		
	(0.172)	(0.154)		
Bank-based tools	-0.200*	-0.221*		
	(0.096)	(0.070)		
Borrower-based · bank-based		0.050		
		(0.393)		
Countercyclical tools			-0.738*	-0.791*
			(0.064)	(0.065)
Cross-sectional tools			-0.100	-0.105
			(0.178)	(0.163)
Countercyclical · cross-sectional				0.044
				(0.627)
Country FE	Yes	Yes	Yes	Yes
Region-time FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
No. of obs.	905	905	905	905
Adj. R^2	0.639	0.639	0.643	0.643
Adj. R^2 within	0.033	0.032	0.044	0.043

[12] Countercyclical tools: countercyclical loan-loss provisions, countercyclical capital buffers, and reserve requirements; cross-sectional tools: loan-to-value ratios, debt-to-income ratios, limits on domestic-currency loans, limits on foreign-currency loans, concentration limits, interbank limits, leverage ratios, a tax on financial institutions, and capital surcharges on SIFIs. The results are robust to classifying loan-to-value and debt-to-income ratios as countercyclical tools (see Table 4.A.5).

By combining tools into an index, the regressions estimate an average effect across all tools. The results in this chapter already suggest that no group of tools is overall detrimental to financial stability. Additionally, I re-run the baseline regression including individual tools (see Table 4.A.6). When including tools one by one, nine out of the twelve tools are negatively related to systemic risk. Four of these relationships are statistically significant. No tool exhibit a significant positive relationship with systemic risk. Similar findings apply when including all individual tools jointly.[13] I thus find no evidence of any tool being detrimental to financial stability.

4.4.4 Heterogeneities across country characteristics

Next, I analyze whether the relationship between macroprudential regulation and systemic risk depends on country characteristics. Table 4.5 reports the results. First, I define an indicator variable for developed countries.[14] Column 1 interacts this indicator variable with macroprudential regulation. The coefficient of macroprudential regulation becomes insignificant while the coefficient of the interaction term is negative and statistically significant. Hence, systemic risk decreases after a tightening of macroprudential regulation only in developed countries. Norring (2019) finds that tightening bank-based macroprudential regulation reduces cross-border lending between advanced economies but increases lending between emerging and developing market economies. If these increased lending activities increase the risk exposure to sudden stops and reversal of capital flows, this result provides one potential explanation for my findings.

Column 2 includes an interaction with a binary variable that indicates boom episodes in the real economy.[15] The coefficients of macroprudential regulation and its interaction with the boom indicator are both statistically significant, yet the coefficient of the single term is negative while the interaction has a positive coefficient. Hence, the full benefits of macroprudential regulation only become visible during bust phases.

Column 3 interacts macroprudential regulation with the measure of financial openness. Both single and interaction terms have negative coefficients, but only that of the interaction

[13]The variation in individual tools is highly limited due to the inclusion of country and region-time fixed effects. I thus refrain from further analyses of individual tools.

[14]Developed countries include upper-middle- and high-income countries as defined by the Worldbank.

[15]The variable is constructed based on turning points of business cycles provided by the OECD.

term is statistically significant. Hence, the higher a country's financial openness, the more systemic risk decreases after macroprudential regulation is tightened. The decrease becomes statistically significant at 50% openness (compare Figure 4.A.3), which applies to two thirds of the sample. The result thus hints at the relevance of the financial interconnectedness of a country.

Conversely, the interconnectedness of the real economy does not play a role. Column 4 interacts macroprudential regulation with *trade* (= sum of imports and exports in % of GDP). Whereas the coefficient of macroprudential regulation remains negative and statistically significant, the interaction term is insignificant. I take these findings as motivation to subsequently explore the role of financial interconnectedness further when analyzing cross-border systemic risk.

Table 4.5: Heterogeneities across country characteristics

Developed country is a binary variable indicating upper-middle and high-income countries. *Boom* indicates boom phases of the real economy. *Financial openness* is a de jure index of capital account openness. *Trade* equals the sum of imports and exports in percent of GDP. Each regression includes the interacted variable also as single term. *Macro controls* further account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. *Additional macro controls* account for inflation, trade, financial openness, government debt to GDP, and the exchange rate. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Macroprudential regulation	0.110	-0.231**	-0.027	-0.185*
	(0.468)	(0.029)	(0.816)	(0.057)
Macroprudential regulation · Developed country	-0.328*			
	(0.055)			
Macroprudential regulation · Boom		0.109*		
		(0.067)		
Macroprudential regulation · Financial openness			-0.002*	
			(0.076)	
Macroprudential regulation · Trade				-0.000
				(0.928)
Country FE	Yes	Yes	Yes	Yes
Region-time FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
No. of obs.	905	905	899	905
Adj. R^2	0.642	0.641	0.636	0.639
Adj. R^2 within	0.040	0.037	0.041	0.031

4.5 Macroprudential regulation and cross-country systemic risk

This section analyzes the relationship between macroprudential regulation and cross-country systemic risk. To this end, I calculate the systemic risk exposure of one country's financial system to another country's financial system based on MES and regress it on macroprudential regulation in the home country and the foreign country.

4.5.1 Relevance of financial interconnectedness

The first analysis in this section estimates my baseline model of cross-border systemic risk, which explains a home country's systemic risk exposure to a foreign country's financial system by macroprudential regulation in the home country and the foreign country while controlling for home country-foreign country, home country-time, and foreign country-time fixed effects, as well as macroeconomic control variables (see Equation 4.4). Table 4.6 reports the results. Irrespective of whether the model includes the standard set of macroeconomic control variables (column 1) or the additional control variables (column 2), macroprudential regulation in the home and in the foreign country is not significantly related to the systemic risk exposure. The same holds when instrumenting for the macroprudential regulation in each country with the political independence and electoral cycle variables, respectively (see column 3 and the first-stage regressions in Table 4.A.7). Hence, cross-country systemic risk exposures do, on average, not decrease with macroprudential regulation. However, the analysis in Section 4.4 highlights that the effects of macroprudential regulation vary greatly across countries. Therefore, I subsequently explore such heterogeneities also for cross-country systemic risk exposures.

To analyze these heterogeneities, I interact macroprudential regulation in the home and foreign countries with country-pair specific characteristics. The additional variation in the resulting interaction terms also allows to include more granular fixed effects. Specifically, the subsequent models include home country-time and foreign country-time instead of the region-time fixed effects.

First, I once more distinguish between developed and developing countries, where the binary variable that indicates developed countries now equals one if both home and foreign country are developed. The coefficients of both interaction terms are negative, but only the interaction with macroprudential regulation in the home country is statistically significant (column 3). This suggests that macroprudential regulation at home can reduce a developed country's systemic risk exposure to another developed country's financial system. While macroprudential regulation abroad does not reduce such spillovers, there is also no evidence that it spurs systemic risk in other countries. Hence, even if regulatory arbitrage leads to a shifting of risks across border (compare, e.g., Ongena, Popov, and Udell (2013)), these negative spillovers appear to get compensated by the positive spillovers from a more stable financial system abroad.

Next, I interact macroprudential regulation at home and abroad with a same-region indicator variable instead of the developed dummy variable. If a home and a foreign country are located within the same geographic region, their financial systems are likely more interconnected. Indeed, MES on average is much lower across regions (0.35) than within regions (0.74). The results are in line with my previous findings. Whereas the home country's macroprudential regulation significantly decreases its cross-country systemic risk exposure, the foreign-country regulation is not significantly related to this exposure (see column 4).

To account for the interconnectedness of financial systems more precisely, column 5 interacts the regulation variables with banks' bilateral cross country claims as a share of the countries' combined GDP. According to the estimates, the cross-border systemic risk exposure significantly increases in the bilateral claims (column 6). More importantly, the coefficient of the interactions with macroprudential regulation is significantly negative for both the home and foreign country. Due to the inclusion of country-time and system-time fixed effects, these estimates only allow to conclude that systemic risk decreases more after regulation tightens if financial systems are more interconnected. To assess at which level of interconnectedness systemic risk decreases overall, column 7 re-estimates the model while including country region-time and system region-time instead of the country-time and system-time fixed effects. The coefficients of the single terms of macroprudential regulation are negative but insignificant whereas the coefficients of the interaction terms remain significantly negative. The systemic risk exposure thus decreases more the more interconnected financial systems are and the decrease is significant already at comparably low levels of interconnectedness (compare Figure 4.A.4).

Table 4.6: Macroprudential regulation and cross-country systemic risk

The regressions analyze the effect of macroprudential regulation in a home *country* and a foreign country's financial *system* on the systemic risk exposure of the home country to the foreign financial system. The results in column 3 are based on an instrumental-variable regression which employs the shares of macroprudential tools whose use is not decided upon by politicians and the electoral cycles in the home country and the foreign country as instruments for the macroprudential regulation in both countries. Table 4.A.7 reports the first-stage regressions. *Developed* indicates upper-middle and high-income countries. *Same region* indicates whether home country and foreign financial system are located within the same geographical region. *Bilateral claims* accounts for the sum of bilateral bank claims as a fraction of the country's and system's combined GDP. Table 4.A.8 tests the robustness of the results with respect to interpolating missing data on bilateral claims. *Macro controls* account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country and system levels. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:				MES			
Country's regulation	-0.009	-0.003	-0.027				-0.005
	(0.587)	(0.868)	(0.415)				(0.736)
System's regulation	-0.004	0.001	-0.022				-0.001
	(0.817)	(0.932)	(0.310)				(0.932)
Country's regulation · Developed				-0.038**			
				(0.019)			
System's regulation · Developed				-0.022			
				(0.238)			
Country's regulation · Same region					-0.017*		
					(0.069)		
System's regulation · Same region					0.002		
					(0.900)		
Country's regulation · Bilateral claims						-1.159***	-2.011***
						(0.006)	(0.005)
System's regulation · Bilateral claims						-0.680**	-1.098**
						(0.047)	(0.014)
Bilateral claims						4.679**	6.861**
						(0.012)	(0.031)
Country-system FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country's region-time FE	Yes	Yes	Yes	No	No	No	Yes
System's region-time FE	Yes	Yes	Yes	No	No	No	Yes
Country-time FE	No	No	No	Yes	Yes	Yes	No
System-time FE	No	No	No	Yes	Yes	Yes	No
Country and system macro controls	Yes	Yes	Yes	No	No	Yes	Yes
Additional country and system controls	No	Yes	No	No	No	No	No
No. of obs.	58,755	53,263	58,755	58,755	58,755	57,934	57,934
Adj. R^2	0.424	0.445	0.424	0.560	0.560	0.563	0.428
Adj. R^2 within	0.003	0.005	-0.000	0.000	0.000	0.001	0.004

4.5.2 Complementarity of home-country and foreign-country regulation

The results in the previous section show that, under certain conditions, systemic risk decreases after macroprudential regulation at home or abroad tightens. The results do not reveal any destabilizing effects of macroprudential regulation that one might suspect due to the shifting of risks across borders caused by regulatory arbitrage. However, regulatory arbitrage may still reduce the effectiveness of macroprudential regulation. To explore this possibility, I subsequently analyze the complementarity of macroprudential regulation at home and abroad.[16]

[16] For an extensive discussion of macroprudential policy spillovers and the scope for international policy coordination, see Agénor and Pereira da Silva (2018).

Table 4.7 reports the regression results. The regressions include home country-foreign country, home country-time, and foreign country-time fixed effects. Column 1 interacts macroprudential regulation in the home country with macroprudential regulation in the foreign country. The coefficient of this term is negative but just insignificant at the conventional levels. Column 2 again distinguishes between developed and developing countries. In line with the previous findings, the coefficient of the interaction between home-country regulation and the developed indicator is negative and statistically significant whereas the interaction for the foreign country is negative but insignificant. More importantly, the coefficient of the interaction between the regulation at home and abroad is negative and statistically significant. Hence, the decrease in systemic risk after a home country tightens its regulation is more pronounced if the regulation abroad is stricter. This is in line with regulatory arbitrage limiting the effectiveness of macroprudential regulation and less opportunities for such arbitrage in case of already strict regulation abroad. The triple interaction with the developed indicator is insignificant. The results thus provide evidence of a complementary relationship between regulation at home and abroad.

Column 3 repeats the exercise but replace the *developed* indicator variable with a same-region dummy variable. The main findings remain unchanged. Lastly, column 4 replaces this dummy variable with bilateral bank claims. As in the previous section, systemic risk decreases in both regulation at home and abroad. In line with the findings in the previous columns, the regulation in both countries are again complements, as the coefficient of the corresponding interaction term is negative and statistically significant. This complementarity is independent of the interconnectedness of the financial systems, which can be concluded from the insignificant triple interaction term.

Overall, the analyses of cross-country systemic risk exposures reveal a complementarity between macroprudential regulation at home and abroad. This finding is in line with regulatory arbitrage limiting the effectiveness of macroprudential regulation without fully negating it.

Table 4.7: Complementarity of macroprudential regulation across countries

The regressions analyze the complementarity of macroprudential regulation in a home *country* and a foreign country's financial *system*. *Developed* indicates upper-middle and high-income countries. *Same region* indicates whether home country and foreign financial system are located within the same geographical region. *Bilateral claims* accounts for the sum of bilateral bank claims as a fraction of the country's and system's combined GDP. *Macro controls* account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country and system levels. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Country's regulation · System's regulation	-0.004	-0.008**	-0.007**	-0.005**
	(0.107)	(0.014)	(0.013)	(0.038)
Country's regulation · Developed		-0.053***		
		(0.007)		
System's regulation · Developed		-0.038		
		(0.114)		
Country's regulation · System's regulation · Developed		0.006		
		(0.196)		
Country's regulation · Same region			-0.041***	
			(0.007)	
System's regulation · Same region			-0.021	
			(0.343)	
Country's regulation · System's regulation · Same region			0.011**	
			(0.020)	
Country's regulation · Bilateral claims				-1.195**
				(0.013)
System's regulation · Bilateral claims				-0.716**
				(0.038)
Country's regulation · System's regulation · Bilateral claims				-0.013
				(0.942)
Bilateral claims				4.795**
				(0.012)
Country-system FE	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes
System-time FE	Yes	Yes	Yes	Yes
No. of obs.	58,755	58,755	58,755	57,934
Adj. R^2	0.560	0.560	0.560	0.563
Adj. R^2 within	0.000	0.000	0.000	0.001

4.6 Additional robustness checks

This section tests the robustness of the results in two regards. First, it repeats the main analyses while applying ΔCoVaR as an alternative systemic risk measure. Then, it analysis the role of the global financial crisis in the sample.

4.6.1 Alternative systemic risk measure

At a regional level, MES and ΔCoVaR evolve similarly over time (compare Figure 4.A.2). To assess whether both measures reveal similar relationships with macroprudential regulation, Table 4.8 repeats main regressions with ΔCoVaR as dependent variable.

Table 4.8: Results for ΔCoVaR as an alternative systemic risk measure

The table displays results for key regressions throughout the paper, but employs ΔCoVaR as systemic risk measure instead of MES. The regression in column 1 analyzes the relationship between macroprudential regulation and systemic risk within a country and follows the specification of the baseline regression (see Table 4.2, column 2). Columns 2 and 3 analyze heterogeneities across macroprudential tools and correspond to the models in Table 4.4, columns 2 and 4. Column 4 replicates the baseline regression of cross-border systemic risk (see Table 4.6, column 1). Column 5 analyzes the complementary between home country and foreign system regulation (compare Table 4.7, column 4). *Macro controls* account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. Table 4.A.1 provides variable definitions. The parentheses report p-values. Standard errors in columns 1 and 2 are clustered at the country level, whereas those in columns 3 to 5 are clustered at the country and system levels. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			ΔCoVaR		
Country's regulation	-0.192*			-0.013	
	(0.066)			(0.161)	
Borrower-based tools		-0.038			
		(0.799)			
Bank-based tools		-0.346*			
		(0.053)			
Borrower-based · bank-based		0.105			
		(0.252)			
Countercyclical tools			0.100		
			(0.768)		
Cross-sectional tools			-0.210**		
			(0.032)		
Countercyclical · cross-sectional			-0.091		
			(0.521)		
System's regulation				-0.009	
				(0.504)	
Country's regulation · System's regulation					-0.001
					(0.568)
Country's regulation · Bilateral claims					0.313
					(0.330)
System's regulation · Bilateral claims					-0.029
					(0.917)
Country's regulation · System's regulation · Bilateral claims					-0.380***
					(0.000)
Bilateral claims					0.710
					(0.389)
Country FE	Yes	Yes	Yes	No	No
Region-time FE	Yes	Yes	Yes	No	No
Country-system FE	No	No	No	Yes	Yes
Country's region-time FE	No	No	No	Yes	No
System's region-time FE	No	No	No	Yes	No
Country-time FE	No	No	No	No	Yes
System-time FE	No	No	No	No	Yes
Macro controls	Yes	Yes	No	Yes	Yes
No. of obs.	866	866	866	61,518	60,239
Adj. R^2	0.899	0.899	0.899	0.938	0.951
Adj. R^2 within	0.027	0.034	0.027	0.007	0.000

Within country, ΔCoVaR decreases significantly after macroprudential regulation is tightened (column 1), thereby providing support for the baseline results based on MES. When distinguishing between bank-based and borrower-based macroprudential tools, ΔCoVaR - just like MES before - emphasizes the role of bank-based tools while providing no indication of the different types of regulation being complements or substitutes: the coefficient of the bank-based tools is negative and statistically significant, whereas borrower based tools and the interaction between the two types do not enter the regressions significantly (column 2). Column 3 distinguishes between countercyclical and cross-sectional tools. ΔCoVaR decreases significantly after the introduction of a cross-sectional tool, but not after the introduction of countercyclical tools. This is different from MES, which emphasized the role of countercyclical tools. I take this finding as further motivation to interpret the role of individual tools conservatively and focus on the overall macroprudential stance. The two measures once more agree that both types of tools are neither substitutes nor complements.

When turning to the analysis of cross-country systemic risk in column 4, ΔCoVaR, in line with MES, is on average across all countries not significantly related to regulation in the home country nor to that in the foreign country. However, column 5 again reveals that regulation at home and abroad are complements, especially in case of highly interconnected financial systems. Hence, I again find support for the need to coordinate macroprudential regulation on a supranational level to protect its effectiveness against limiting factors such as the cross-border shifting of risks due to regulatory arbitrage.

4.6.2 The global financial crisis

The global financial crisis marks an exceptional event in terms of financial stability. While my regressions include (region-) country-time fixed effects, I subsequently explore the robustness of my results by excluding 2008, the year during which the systemic risk measures spike (compare Figure 4.A.2). Table 4.9 reports the results.

As before, systemic risk decreases significantly after macroprudential regulation is tightened (see column 1). The cross-country systemic risk exposure is not significantly related to macroprudential regulation in the home or foreign country (column 2), unless the financial systems of both countries are sufficiently interconnected (column 3). Both results again support the earlier findings. Lastly, I once more find evidence of a complementary relationship between macroprudential regulation at home and abroad (column 4). Overall, the results prove highly robust such that the findings are not driven by the global financial crisis.

Table 4.9: Results when excluding the global financial crisis

The table displays results for key regressions throughout the paper, but excludes the time of the global financial crisis in 2008, during which systemic risk spikes (see Figure 4.A.2). The regression in column 1 analyzes the relationship between macroprudential regulation and systemic risk within a country and corresponds to the baseline regression in Table 4.2, column 2. Column 2 replicates the baseline regression of cross-border systemic risk (see Table 4.6, column 1). Column 3 illustrates the dependence of the cross-country effect of regulation on the interconnectedness of home- and foreign-country financial systems (see Table 4.6, column 7). Column 4 analyzes the complementary between home country and foreign system regulation (compare Table 4.7, column 4). *Macro controls* account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. Table 4.A.1 provides variable definitions. The parentheses report p-values. Standard errors in columns 1 and 2 are clustered at the country level, whereas those in columns 3 and 4 are clustered at the country and system levels. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Country's regulation	-0.193*	-0.012	-0.009	
	(0.057)	(0.418)	(0.544)	
System's regulation		-0.014	-0.012	
		(0.451)	(0.521)	
Country's regulation · Bilateral claims			-1.834***	-1.179**
			(0.003)	(0.018)
System's regulation · Bilateral claims			-0.910**	-0.537*
			(0.018)	(0.072)
Country's regulation · System's regulation				-0.005**
				(0.036)
Country's regulation · System's regulation · Bilateral claims				-0.015
				(0.929)
Country FE	Yes	No	No	No
Region-time FE	Yes	No	No	No
Country-system FE	No	Yes	Yes	Yes
Country's region-time FE	No	Yes	Yes	No
System's region-time FE	No	Yes	Yes	No
Country-time FE	No	No	No	Yes
System-time FE	No	No	No	Yes
Macro controls	Yes	Yes	Yes	Yes
No. of obs.	840	54,557	53,736	53,736
Adj. R^2	0.615	0.334	0.338	0.462
Adj. R^2 within	0.038	0.003	0.004	0.000

4.7 Conclusion

This paper analyzes the effects of macroprudential regulation on financial stability. While the previous literature focuses on intermediate variables that are related to financial crises such as credit and house-price growth, I analyze the effect of macroprudential regulation on explicit measures of systemic risk. These measures simultaneously allow for desired stabilizing effects and fragility emerging due to regulatory arbitrage and the regulation-induced shifting of risks, thereby complementing the literature with an overall assessment of the regulations' consequences for financial stability.

I find that tighter macroprudential regulation reduces systemic risk, especially in developed countries, when bank-based tools are applied, and when countries are financially interconnected. No macroprudential tool consistently increases systemic risk and the analysis provides no evidence of complementary effects of individual tools. In contrast, the results indicate that macroprudential regulation at home and abroad complement each other. If the financial systems of two countries are sufficiently interconnected, a tighter regulation in a home country can reduce its financial system's systemic risk exposures to other countries' financial systems, especially when regulation abroad is also strict and, hence, the potential for regulatory arbitrage across country borders is limited. In addition to supporting the effectiveness of home-country regulation, macroprudential regulation abroad also reduces the home country's systemic risk exposure, although to a lesser degree than the regulation in that country.

The results suggest several implications. First, the benefits of macroprudential regulation outweigh its negative effects on financial stability such that regulatory arbitrage and the shifting of risks can serve as motivation for a careful use of macroprudential tools, but not as an argument against macroprudential regulation itself. Second, the results call for supranational coordination of macroprudential regulation to increase the effectiveness of the regulation by limiting regulatory arbitrage across countries. Third, while a welfare analysis is beyond the scope of this paper, the large heterogeneity of the effectiveness of macroprudential regulation across country characteristics suggests that tighter macroprudential regulation may not always be optimal. And lastly, the fact that the use of macroprudential tools is subject to political constraints may motivate the choice of an institutional framework that guarantees political independence to activate macroprudential tools when needed to optimally contribute to systemic financial stability.

4.A Appendix: additional figures and tables

Figure 4.A.1: The relationship between MES and macroprudential regulation

The binned scatter plot illustrates the relationship between MES and macroprudential regulation as estimated in the baseline regression (see Table 4.2, column 2). The plot is obtained by partialling out country fixed effects, region-time fixed effects, and the macroeconomic control variables. Each dot represents 9 observations.

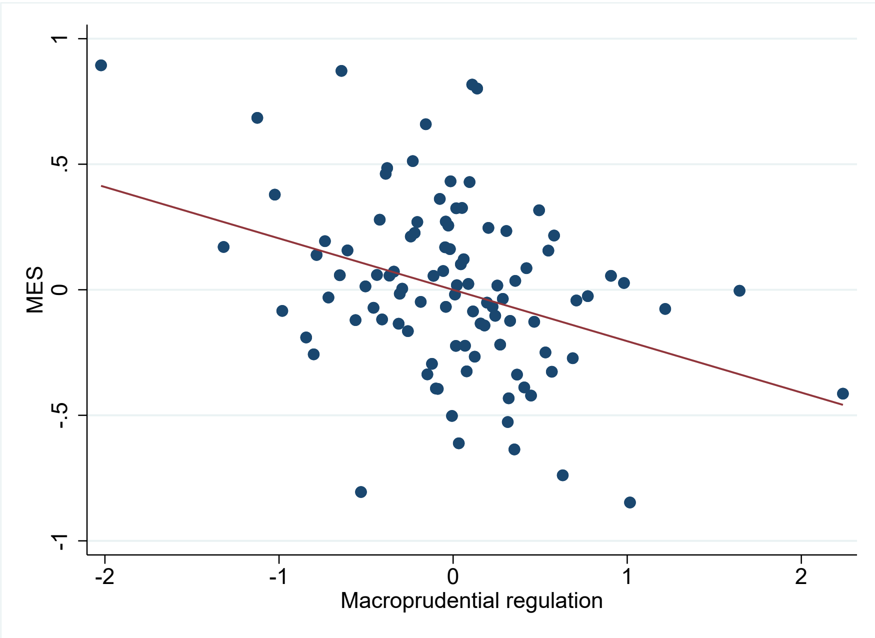


Figure 4.A.2: The evolution of MES and ΔCoVaR

The figure displays the evolution of the unweighted means of MES and ΔCoVaR in daily percent and weekly percentage points across countries within the regions indicated above each figure. Section 4.3.1 elaborates on the estimation of the systemic risk measures.

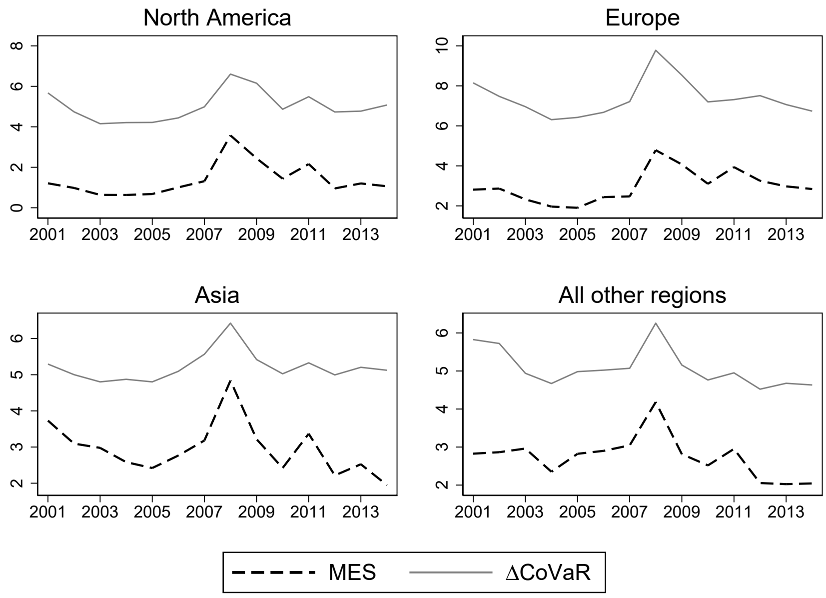


Figure 4.A.3: Marginal effect of macroprudential regulation across financial openness

The figure illustrates the marginal effect of macroprudential regulation on MES in dependence of a country's de jure capital account openness. The estimates are based on the regression reported in Table 4.5, column 3, which controls for country fixed effects, region-time fixed effects, GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate.

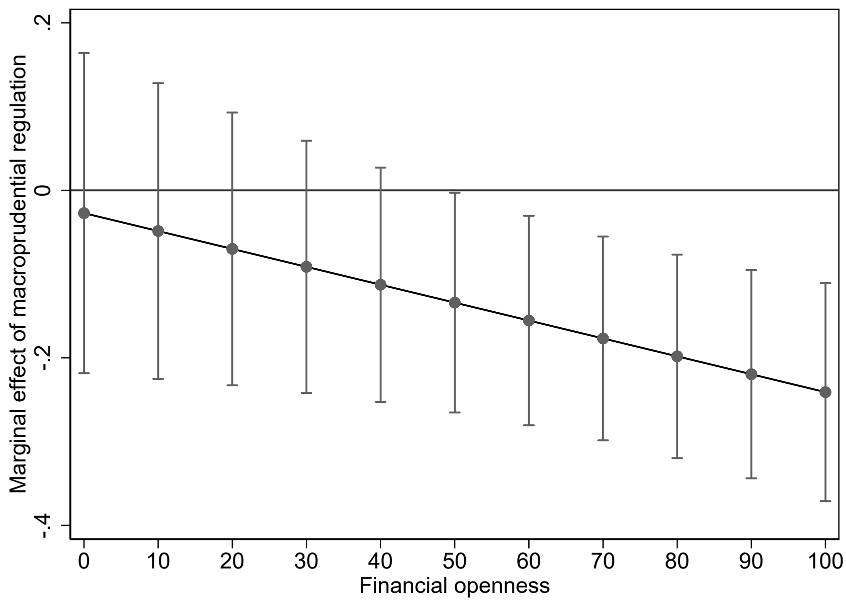
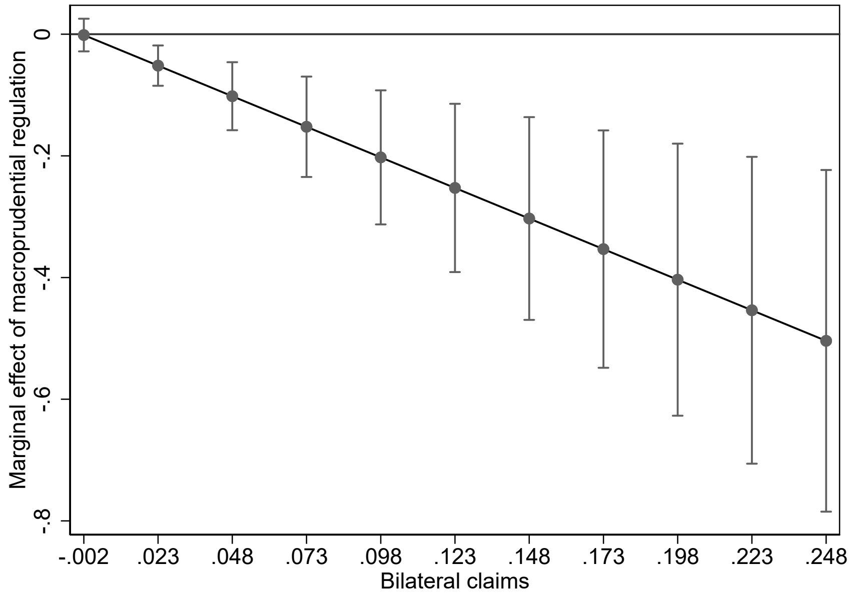


Figure 4.A.4: Marginal effect of macroprudential regulation across bilateral claims

The figure illustrates the marginal effect of macroprudential regulation in a home country on the country's systemic risk exposure to a foreign financial system in dependence of the financial interconnectedness between the country and the system. This risk exposure is estimated by MES. The financial interconnectedness is proxied by bilateral bank claims between the two countries as a fraction of their combined GDP. The estimates are based on the regression reported in Table 4.6, column 7.

(a) Macroprudential regulation in the home country



(b) Macroprudential regulation in the foreign country

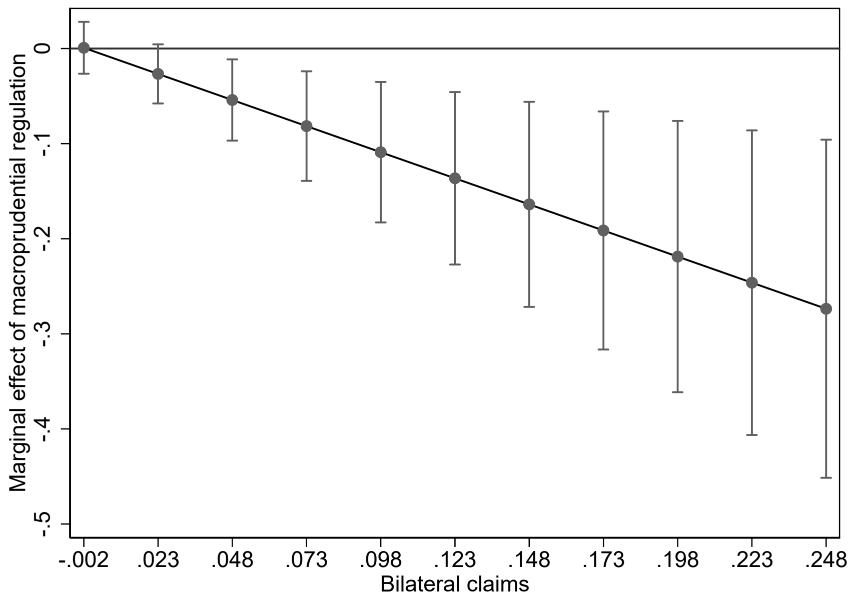


Table 4.A.1: Variable definitions and data sources

Section 4.3.1 describes the variables in detail. Table 4.1 reports summary statistics.

Variable name	**Description**
Dependent variables	
MES	Marginal expected shortfall; winsorized at 1%/99% before aggregation at country level; estimation strategy provided in Section 4.3.1. Source of market equity data: Thomson Reuter's Eikon.
ΔCoVaR	Change in the conditional value at risk; estimation strategy provided in Section 4.3.1. Source of market equity data: Thomson Reuter's Eikon.
Main explanatory variables	
Macroprudential regulation	Number of macroprudential tools that are currently used in a country (see Section 4.3.1). Source: Cerutti, Claessens, and Laeven (2017).
Country's regulation	*Macroprudential regulation* (see above) in the country whose banks are treated as risk recipient by MES.
System's regulation	*Macroprudential regulation* (see above) in the country whose financial system is treated as risk inducer by MES.
Instruments	
% non-politician	Share of instruments whose use is not decided upon by politicians. Sources: Cerutti, Claessens, and Laeven (2017) and various policy documents.
Election	Indicates upcoming elections and equals the share of quarters in a year that are no further than one year from the next election. Source of election dates: Müller (2019).
Further macroeconomic variables	
Banking crisis	Indicator variable that equals one during banking crises. Source: Laeven and Valencia (2018).
Bilateral claims	Sum of bilateral bank claims as a fraction of the sum of both countries' GDP. Sources: BIS (Locational Banking Statistics), own calculation.
Credit-to-GDP growth	Yearly credit-to-GDP growth [in%]; credit refers to the financial sector's domestic credit. Source: Worldbank.
Developed (country)	Binary variable indicating upper-middle and high-income countries as classified by the Worldbank.
Exchange rate	Real USD exchange rate: nominal exchange rate in units of national currency per USD · (U.S. CPI / local CPI). Source: IMF.
Financial openness	De jure index of capital account openness [in % of the maximum openness in the sample]. Source: Chinn and Ito (2006), updated.
Government debt to GDP	Public debt to GDP [in %]. Source: IMF Historical Public Debt Database.
Inflation	Inflation based on the consumer price index. Source: Worldbank.
Monetary policy rate	Monetary policy rate [in%]. Sources: Datastream, OECD, IMF, BIS.
Real GDP growth	Yearly real GDP growth [in%]; source: Worldbank.
Trade	Sum of imports and exports in percent of GDP. Source: Worldbank.

Table 4.A.2: Correlations between macroprudential tools

The statistics are computed for the baseline sample (see the summary statistics in Table 4.1). The macroprudential tools are discussed in Section 4.3.1. *CCyB*: countercyclical capital buffer; *CCyLLP*: countercyclical loan-loss provisions; *DTI*: debt-to-income ratios; *LTV*: loan-to-value ratios; *Loan limits*: limits on domestic-currency loans; *FX loan limits*: limits on foreign-currency loans; *CCL*: concentration limits; *Interbank limits*: limits on interbank exposures; *Leverage*: leverage ratios; *RR*: reserve requirements; *Tax*: tax on financial institutions; *SIFI*: capital surcharges on systemically important financial institutions.

	(1)											
	CCyB	CCyLLP	DTI	LTV	Loan limits	FX loan limits	CCL	Interbank limits	Leverage	RR	Tax	SIFI
CCyB	1											
CCyLLP	-0.0271	1										
DTI	0.216***	0.206***	1									
LTV	0.104**	0.247***	0.448***	1								
Loan limits	0.315***	-0.0691*	0.106**	0.170***	1							
FX loan limits	0.141***	0.0237	0.244***	0.167***	0.149***	1						
CCL	0.0326	0.168***	0.209***	0.0495	0.0683*	0.178***	1					
Interbank limits	0.0909**	0.0661*	0.142***	0.0107	0.0170	0.310***	0.351***	1				
Leverage	-0.00939	-0.0450	0.222***	-0.0105	-0.104**	0.0273	0.102**	0.184***	1			
RR	0.0650	0.0802*	-0.0427	-0.0790*	0.176***	0.178***	0.144***	0.124***	-0.0635	1		
Tax	0.135***	0.0881**	0.262***	0.296***	0.163***	0.237***	0.186***	0.142***	0.0586	-0.0963**	1	
SIFI	0.0905**	0.217***	0.102**	0.101**	-0.0283	-0.00417	0.0849*	0.0639	0.136***	0.0417	0.0593	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.A.3: Macroprudential regulation and systemic risk: control variables

The table restates the regressions presented in Table 4.2, but also reports the coefficients of the control variables. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Macroprudential regulation	-0.205**	-0.184*	-0.133*	-0.152*
	(0.048)	(0.058)	(0.073)	(0.080)
Macroprudential regulation^2				0.008
				(0.607)
Real GDP growth		-0.001	0.005	0.006
		(0.947)	(0.816)	(0.800)
Credit-to-GDP growth		-0.000	-0.000	-0.000
		(0.761)	(0.617)	(0.617)
Banking crisis		0.532*	0.434	0.435
		(0.060)	(0.120)	(0.120)
Monetary policy rate		0.030	0.000	-0.001
		(0.108)	(0.999)	(0.959)
Inflation			0.016	0.015
			(0.332)	(0.341)
Trade			0.002	0.002
			(0.539)	(0.522)
Financial openness			-0.006	-0.006
			(0.353)	(0.350)
Government debt to GDP			0.009**	0.009**
			(0.046)	(0.046)
Exchange rate			-0.000	-0.000
			(0.153)	(0.143)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No
Region-time FE	No	No	Yes	Yes
No. of obs.	905	905	861	861
Adj. R^2	0.633	0.640	0.653	0.652
Adj. R^2 within	0.017	0.034	0.051	0.050

Table 4.A.4: Instrumental-variable approach: first-stage regressions

The table displays the first-stage estimates of the instrumental-variable regressions reported in Table 4.3, which also contains F-values from tests for joint significance of the instruments and p-values for Hansen's test of overidentifying restrictions. In column 3, the elections instrumental variable is exclusively based on elections that take place at the end of the regular term. Column 4 defines the election variable as an indicator variable equal to one during election years. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	Macroprudential regulation			
% non-politician	0.023***	0.021***	0.021***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
Election	-0.091*	-0.114**		
	(0.077)	(0.021)		
Election after full term			-0.121**	
			(0.020)	
Election in Q4				-0.168**
				(0.017)
Real GDP growth	0.030**	0.019	0.019	0.019
	(0.045)	(0.264)	(0.268)	(0.266)
Credit-to-GDP growth	0.001**	0.001***	0.001***	0.001***
	(0.012)	(0.008)	(0.008)	(0.008)
Banking crisis	-0.084	0.056	0.052	0.057
	(0.648)	(0.786)	(0.801)	(0.783)
Monetary policy rate	-0.025	-0.008	-0.008	-0.008
	(0.100)	(0.659)	(0.650)	(0.640)
Inflation		-0.015	-0.015	-0.015
		(0.120)	(0.121)	(0.136)
Trade		0.004	0.004	0.003
		(0.446)	(0.443)	(0.450)
Financial openness		0.008*	0.008*	0.008*
		(0.058)	(0.056)	(0.057)
Government debt to GDP		-0.011**	-0.011**	-0.011**
		(0.023)	(0.023)	(0.025)
Exchange rate		0.000	0.000	0.000
		(0.656)	(0.653)	(0.657)
Country FE	Yes	Yes	Yes	Yes
Region-time FE	Yes	Yes	Yes	Yes
No. of obs.	657	616	616	616
Adj. R^2	0.897	0.903	0.903	0.903
Adj. R^2 within	0.309	0.382	0.383	0.383

Table 4.A.5: Heterogeneity across macroprudential tools: alternative classification

Columns 1 and 2 restate the regressions reported in Table 4.4, columns 3 and 4. Columns 3 and 4 re-estimate the regressions but classify loan-to-value and debt-to-income ratios as countercyclical instead of cross-sectional tools. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
	Baseline		Alternative	
Countercyclical tools	-0.738*	-0.791*	-0.280*	-0.281*
	(0.064)	(0.065)	(0.080)	(0.085)
Cross-sectional tools	-0.100	-0.105	-0.084	-0.085
	(0.178)	(0.163)	(0.337)	(0.367)
Countercyclical · cross-sectional		0.044		0.002
		(0.627)		(0.972)
Country FE	Yes	Yes	Yes	Yes
Region-time FE	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
No. of obs.	905	905	905	905
Adj. R^2	0.643	0.643	0.640	0.640
Adj. R^2 within	0.044	0.043	0.036	0.034

Table 4.A.6: Estimates for individual macroprudential tools

The regressions in this table follow the baseline specification (see Table 4.2, column 2), but include individual macroprudential tools instead the of overall index. The results in column 1 are obtained by including only one tool at a time. In column 2, all tools are included jointly. > 0 or < 0 indicates the sign of coefficients that are not statistically significant at the usual significance levels. Coefficients represented by numbers are statistically significant at least at the 10% level. The macroprudential tools are discussed in Section 4.3.1. *CCyB*: countercyclical capital buffer; *CCyLLP*: countercyclical loan-loss provisions; *DTI*: debt-to-income ratios; *LTV*: loan-to-value ratios; *Loan limits*: limits on domestic-currency loans; *FX loan limits*: limits on foreign-currency loans; *CCL*: concentration limits; *Interbank limits*: limits on interbank exposures; *Leverage*: leverage ratios; *RR*: reserve requirements; *Tax*: tax on financial institutions; *SIFI*: capital surcharges on systemically important financial institutions. *Macro controls* account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. Table 4.A.1 provides variable definitions.

	(1)	(2)
Dependent variable:	MES	
Tools included jointly?	No	Yes
CCyB	> 0	< 0
CCyLLP	-1.19	-1.03
DTI	-.44	< 0
LTV	< 0	> 0
Loan limits	> 0	> 0
FX loan limits	< 0	< 0
CCL	< 0	< 0
Interbank limits	< 0	< 0
Leverage	< 0	< 0
RR	-1.03	-.72
Tax	> 0	> 0
SIFI	-.46	< 0
Country FE	Yes	Yes
Region-time FE	Yes	Yes
Macro controls	Yes	Yes

Table 4.A.7: Cross-country systemic risk: first-stage regressions

The table displays the first-stage estimates of the instrumental-variable regression reported in Table 4.6, column 3. *Macro controls* account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country and system levels. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)
Dependent variable:	Macroprudential regulation in country	Macroprudential regulation in system
% non-politician (country)	0.021***	0.000
	(0.000)	(0.947)
Election (country)	-0.098**	0.000
	(0.022)	(0.416)
% non-politician (system)	0.000	0.022***
	(0.853)	(0.000)
Election (system)	-0.000**	-0.093**
	(0.020)	(0.028)
Country-system FE	Yes	Yes
Country's region-time FE	Yes	Yes
System's region-time FE	Yes	Yes
Macro controls	Yes	Yes
No. of obs.	58,755	58,755
Adj. R^2	0.905	0.906
Adj. R^2 within	0.210	0.210

Table 4.A.8: Cross-country systemic risk and financial interconnectedness: robustness

Columns 1 and 2 restate the regressions reported in Table 4.6, columns 6 and 7. Columns 3 and 4 re-estimate the regressions but exclude all country-system pairs that are not fully covered in the original Locational Banking Statistics data. *Macro controls* account for GDP growth, credit-to-GDP growth, banking crises, and the monetary policy rate. Table 4.A.1 provides variable definitions. The parentheses report p-values based on standard errors clustered at the country and system levels. ***, **, * indicate significance at the 1%, 5% and 10% levels.

	(1)	(2)	(3)	(4)
Dependent variable:	MES			
Country's regulation		-0.005		-0.015
		(0.736)		(0.553)
System's regulation		-0.001		-0.011
		(0.932)		(0.546)
Country's regulation · Bilateral claims	-1.159***	-2.011***	-0.783***	-1.532**
	(0.006)	(0.005)	(0.002)	(0.020)
System's regulation · Bilateral claims	-0.680**	-1.098**	-0.483*	-0.522
	(0.047)	(0.014)	(0.054)	(0.169)
Bilateral claims	4.679**	6.861**	3.704**	5.472**
	(0.012)	(0.031)	(0.021)	(0.049)
Country-system FE	Yes	Yes	Yes	Yes
Country's region-time FE	No	Yes	No	Yes
System's region-time FE	No	Yes	No	Yes
Country-time FE	Yes	No	Yes	No
System-time FE	Yes	No	Yes	No
Country and system macro controls	Yes	Yes	Yes	Yes
No. of obs.	57,934	57,934	20,236	20,238
Adj. R^2	0.563	0.428	0.748	0.565
Adj. R^2 within	0.001	0.004	0.001	0.006

Bibliography

Acharya, Viral V., Katharina Bergant, Matteo Crosignani, Tim Eisert, and Fergal McCann (2020). "The Anatomy of the Transmission of Macroprudential Policies". *NBER Working Paper* 27292.

Acharya, Viral V., Robert Engle, and Matthew Richardson (2012). "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks". *American Economic Review: Papers and Proceedings* 102.3, pp. 59–64.

Acharya, Viral V., Douglas Gale, and Tanju Yorulmazer (2011). "Rollover Risk and Market Freezes". *Journal of Finance* 66.4, pp. 1177–1209.

Acharya, Viral V., Lasse H. Pedersen, Thomas Philippon, and Matthew Richardson (2017). "Measuring Systemic Risk". *Review of Financial Studies* 30.1, pp. 2–47.

Acharya, Viral V. and S. Viswanathan (2011). "Leverage, Moral Hazard, and Liquidity". *Journal of Finance* 66.1, pp. 99–138.

Adrian, Tobias and Markus K. Brunnermeier (2016). "CoVaR". *American Economic Review* 106.7, pp. 1705–1741.

Adrian, Tobias, Fernando Duarte, Nellie Lian, and Pawel Zabczyk (2020). "Monetary and Macroprudential Policy with Endogenous Risk". *CEPR Discussion Papers* 14435.

Adrian, Tobias and Hyun Song Shin (2010). "Liquidity and Leverage". *Journal of Financial Intermediation* 19.3, pp. 418–437.

Agarwal, Sumit and Robert Hauswald (2010). "Distance and Private Information in Lending". *Review of Financial Studies* 23.7, pp. 2757–2788.

Agénor, Pierre-Richard and Luiz A Pereira da Silva (2018). "Financial Spillovers, Spillbacks, and the Scope for International Macroprudential Policy Coordination". *BIS Papers* 97.

Ahnert, Toni, Kristin J. Forbes, Christian Friedrich, and Dennis Reinhardt (2021). "Macroprudential FX Regulations: Shifting the Snowbanks of FX Vulnerability?" *Journal of Financial Economics* 140.1, pp. 145–174.

Ahuja, Ashvin and Malhar Nabar (2011). "Safeguarding Banks and Containing Property Booms: Cross-Country Evidence on Macroprudential Policies and Lessons from Hong Kong SAR". *IMF Working Paper* 11/284.

Aikman, David, Jonathan Bridges, Anil Kashyap, and Caspar Siegert (2019a). "Is a macroprudential reaction function emerging and is it sensible?" *Unpublished Manuscript*.

— (2019b). "Would Macroprudential Regulation Have Prevented the Last Crisis?" *Journal of Economic Perspectives* 33.1, pp. 107–130.

Aiyar, Shekhar, Charles W. Calomiris, and Tomasz Wieladek (2014). "Does Macroprudential Regulation Leak? Evidence from a UK Policy Experiment". *Journal of Money, Credit and Banking* 46.s1, pp. 181–214.

Allen, Franklin, Ana Babus, and Elena Carletti (2012). "Financial Connections and Systemic Risk". In: *Market Institutions and Financial Market Risk*. Ed. by Mark Carey, Anil Kashyap, Raghuram G. Rajan, and René M. Stulz. NBER Books. National Bureau of Economic Research, Inc.

Allen, Franklin and Douglas Gale (1994). "Limited Market Participaton and Volatility of Asset Prices". *American Economic Review* 84.4, pp. 933–955.

— (2007). *Understanding Financial Crises*. New York: Oxford University Press Inc.

Allen, Linda, Turan G. Bali, and Yi Tang (2012). "Does Systemic Risk in the Financial Sector Predict Future Economic Downturns?" *Review of Financial Studies* 25.10, pp. 3000–3036.

Altunbas, Yener, Mahir Binici, and Leonardo Gambacorta (2018). "Macroprudential Policy and Bank Risk". *Journal of International Money and Finance* 81, pp. 203–220.

Avdjiev, Stefan, Cathérine Koch, Patrick McGuire, and Goetz von Peter (2017). "International Prudential Policy Spillovers: A Global Perspective". *International Journal of Central Banking* 13.2, pp. 5–33.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong (2018a). "Social Connectedness: Measurement, Determinants, and Effects". *Journal of Economic Perspectives* 32.3, pp. 259–280.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel (2018b). "The Economic Effects of Social Networks: Evidence from the Housing Market". *Journal of Political Economy* 126.6, pp. 2224–2276.

Bailey, Michael, Abhinav Gupta, Sebastian Hillenbrand, Theresa Kuchler, Robert Richmond, and Johannes Stroebel (2021). “International Trade and Social Connectedness”. *Journal of International Economics* 129.103418.

Bailey, Michael, Drew Johnston, Theresa Kuchler, Johannes Stroebel, and Arlene Wong (2019). “Peer Effects in Product Adoption”. *NBER Working Paper* 25843.

Barth, Andreas and Isabel Schnabel (2013). “Why Banks Are not too Big to Fail: Evidence from the CDS Market”. *Economic Policy* 28.74, pp. 335–369.

Basten, Christoph (2020). “Higher Bank Capital Requirements and Mortgage Pricing: Evidence from the Counter-Cyclical Capital Buffer”. *Review of Finance* 24.2, pp. 453–495.

Baum-Snow, Nathanial (2007). “Did Highways Cause Suburbanization?” *Quarterly Journal of Economics* 122.2, pp. 775–805.

Beck, T., H. Degryse, R. de Haas, and N. van Horen (2018). “When arm’s length is too far: Relationship banking over the credit cycle”. *Journal of Financial Economics* 127.1, pp. 174–196.

Beck, Thorsten, Steven Ongena, and İlkay Şendeniz-Yüncü (2019). “Keep Walking? Geographical Proximity, Religion, and Relationship Banking”. *Journal of Corporate Finance* 55, pp. 49–68.

Benoit, Sylvain, Gilbert Colletaz, Christophe Hurlin, and Christophe Pérignon (2013). “A Theoretical and Empirical Comparison of Systemic Risk Measures”. *HEC Paris Research Paper* FIN-2014-1030.

Berger, Allen N., Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan, and Jeremy C. Stein (2005). “Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks”. *Journal of Financial Economics* 76.2, pp. 237–269.

Bernanke, Ben and Mark Gertler (1989). “Agency Costs, Net Worth, and Business Fluctuations”. *American Economic Review* 79.1, pp. 14–31.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1999). “The Financial Accelerator in a Quantitative Business Cycle Framework”. *In: Handbook of Macroeconomics* edited by: John B. Taylor and Michael Woodford, 1, pp. 1341–1393.

Bernardi, M., G. Gayraud, and L. Petrella (2013). “Bayesian Inference for CoVaR”. *Working Paper*.

Bianchi, Javier and Enrique G. Mendoza (2020). “A Fisherian Approach to Financial Crises: Lessons from the Sudden Stops Literature”. *NBER Working Paper* 26915.

Bisias, Dimitrios, Mark Flood, Andrew W. Lo, and Stavros Valavanis (2012). "A Survey of Systemic Risk Analytics". *Annual Review of Financial Economics* 4.1, pp. 255–296.

Bohl, Martin T., Philipp Kaufmann, and Patrick M. Stephan (2013). "From Hero to Zero: Evidence of Performance Reversal and Speculative Bubbles in German Renewable Energy Stocks". *Energy Economics* 37, pp. 40–51.

Boot, Arnoud W.A. (2000). "Relationship Banking: What Do We Know?" *Journal of Financial Intermediation* 9.1, pp. 7–25.

Bordo, Michael D. and O. Jeanne (2002). "Monetary Policy and Asset Prices: Does 'Benign Neglect' Make Sense?" *International Finance* 5.2, pp. 139–164.

Borio, Claudio and Philip Lowe (2002). "Asset Prices, Financial and Monetary Stability: Exploring the Nexus". *BIS Working Papers* 114.

Breitung, Jörg and Ulrich Homm (2012). "Testing for Speculative Bubbles in Stock Markets: A Comparison of Alternative Methods". *Journal of Financial Econometrics* 10.1, pp. 198–231.

Brevoort, Kenneth P. and Timothy H. Hannan (2006). "Commercial Lending and Distance: Evidence from Community Reinvestment Act Data". *Journal of Money, Credit and Banking* 38.8, pp. 1991–2012.

Brown, Jeffrey R., Zoran Ivković, Paul A. Smith, and Scott J. Weisbenner (2008). "Neighbors Matter: Causal Community Effects and Stock Market Participation". *Journal of Finance* 63.3, pp. 1509–1531.

Brownlees, Christian and Robert F. Engle (2017). "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk". *Review of Financial Studies* 30.1, pp. 48–79.

Brunnermeier, Markus K. (2009). "Deciphering the Liquidity and Credit Crunch 2007–2008". *Journal of Economic Perspectives* 23.1, pp. 77–100.

Brunnermeier, Markus K., Gang N. Dong, and Darius Palia (2020). "Banks' Noninterest Income and Systemic Risk". *Review of Corporate Finance Studies* 9.2, pp. 229–255.

Brunnermeier, Markus K. and Martin Oehmke (2013). "Bubbles, Financial Crises, and Systemic Risk". In: *Handbook of the Economics of Finance*. Ed. by George M. Constantinides, Milton Harris, and René M. Stulz. Vol. 2. Amsterdam and London: North Holland, pp. 1221–1288.

Brunnermeier, Markus K. and Lasse H. Pedersen (2009). "Market Liquidity and Funding Liquidity". *Review of Financial Studies* 22.6, pp. 2201–2238.

Brunnermeier, Markus K., Simon Rother, and Isabel Schnabel (2020). "Asset Price Bubbles and Systemic Risk". *Review of Financial Studies* 33.9, pp. 4272–4317.

Brunnermeier, Markus K. and Yuliy Sannikov (2014). "A Macroeconomic Model with a Financial Sector". *American Economic Review* 104.2, pp. 379–421.

Brunnermeier, Markus K. and Isabel Schnabel (2016). "Bubbles and Central Banks: Historical Perspectives". In: *Central Banks at a Crossroads - What Can We Learn from History?* Ed. by Michael D. Bordo, Oyvind Eitrheim, Marc Flandreau, and Jan F. Qvigstad. Cambridge: Cambridge University Press, pp. 493–562.

Buch, Claudia M. and Linda S. Goldberg (2017). "Cross-Border Prudential Policy Spillovers: How Much? How Important? Evidence from the International Banking Research Network". *International Journal of Central Banking* 13.2, pp. 505–558.

Busetti, Fabio and A. M. Robert Taylor (2004). "Tests of Stationarity Against a Change in Persistence". *Journal of Econometrics* 123.1, pp. 33–66.

Cameron, Colin A. and Douglas L. Miller (2014). "Robust Inference for Dyadic Data". *Working Paper*.

Cao, Z. (2013). "Multi-CoVaR and Shapley Value: A Systemic Risk Approach". *Working Paper*.

Capuano, Christian (2008). "The Option-iPoD: The Probability of Default Implied by Option Prices Based on Entropy". *IMF Working Paper* 08/194.

Cerutti, Eugenio, Stijn Claessens, and Luc Laeven (2017). "The Use and Effectiveness of Macroprudential Policies: New Evidence". *Journal of Financial Stability* 28, pp. 203–224.

Chaney, Thomas (2014). "The Network Structure of International Trade". *American Economic Review* 104.11, pp. 3600–3634.

Chinn, Menzie D. and Hiro Ito (2006). "What Matters for Financial Development? Capital Controls, Institutions, and Interactions". *Journal of Development Economics* 81.1.

Claessens, Stijn, Swati R. Ghosh, and Roxana Mihet (2013). "Macro-prudential Policies to Mitigate Financial System Vulnerabilities". *Journal of International Money and Finance* 39, pp. 153–185.

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy (2008). "The Small World of Investing: Board Connections and Mutual Fund Returns". *Journal of Political Economy* 116.5, pp. 951–979.

— (2010). "Sell-Side School Ties". *Journal of Finance* 65.4, pp. 1409–1438.

Collins, M. (1992). “Overend Gurney Crisis, 1866”. In: *The New Palgrave Dictionary of Money and Finance*. Ed. by P. Newman. Palgrave Macmillan.

de Bandt, Olivier and Philipp Hartmann (2000). “Systemic risk: A survey”. *ECB Working Paper* 35.

Degryse, Hans, Luc Laeven, and Steven Ongena (2009). “The Impact of Organizational Structure and Lending Technology on Banking Competition”. *Review of Finance* 13.2, pp. 225–259.

Degryse, Hans and Steven Ongena (2005). “Distance, Lending Relationships, and Competition”. *Journal of Finance* 60.1, pp. 231–266.

Demirgüç-Kunt, Asli and Enrica Detragiache (1998). “The Determinants of Banking Crises in Developing and Developed Countries”. *IMF Staff Papers* 45.1.

DeYoung, Robert, Dennis Glennon, and Peter Nigro (2008). “Borrower–Lender Distance, Credit Scoring, and Loan Performance: Evidence From Informational-Opaque Small Business Borrowers”. *Journal of Financial Intermediation* 17.1, pp. 113–143.

Diamond, Douglas W. (1984). “Financial Intermediation and Delegated Monitoring”. *Review of Economic Studies* 51.3, pp. 393–414.

Diamond, Douglas W. and Philip H. Dybvig (1983). “Bank Runs, Deposit Insurance, and Liquidity”. *Journal of Political Economy* 91.3, pp. 401–419.

Diamond, Douglas W. and Raghuram G. Rajan (2011). “Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes”. *Quarterly Journal of Economics* 126.2, pp. 557–591.

Diba, Behzad T. and Herschel I. Grossman (1988). “Explosive Rational Bubbles in Stock Prices?” *American Economic Review* 78.3, pp. 520–530.

Donaldson, Dave and Richard Hornbeck (2016). “Railroads and American Economic Growth: A “Market Access” Approach”. *Quarterly Journal of Economics* 131.2, pp. 799–858.

Drehmann, Mathias, Claudio Borio, and Kostas Tsatsaronis (2012). “Characterising the Financial Cycle: Don’t Lose Sight of the Medium Term!” *BIS Working Papers* 380.

Duflo, Esther and Emmanuel Saez (2003). “The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment”. *Quarterly Journal of Economics* 118.3, pp. 815–842.

Elazar, Daniel J. (1984). *American Federalism*. 3rd ed. New York: Harper and Row.

Engle, Robert, Eric Jondeau, and Michael Rockinger (2015). “Systemic Risk in Europe”. *Review of Finance* 19.1, pp. 145–190.

Etienne, Xiaoli L., Scott H. Irwin, and Philip Garcia (2014). “Bubbles in Food Commodity Markets: Four Decades of Evidence”. *Journal of International Money and Finance* 42, pp. 129–155.

Farhi, Emanuel and Ivan Werning (2016). “A Theory of Macroprudential Policies in the Presence of Nominal Rigidities”. *Econometrica* 84.5.

Fenner, Arved, Philipp Klein, and Carina Mössinger (2019). “Digging into the Black Box of Portfolio Replenishment in Securitization: Evidence from the ABS Loan-Level Initiative”. *Working Paper*.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig (2017). “Cultural Proximity and Loan Outcomes”. *American Economic Review* 107.2, pp. 457–492.

Forbes, Kristin J. (2019). “Macroprudential Policy: What We’ve Learned, Don’t Know, and Need to Do”. *AEA Papers and Proceedings* 109, pp. 470–475.

— (2020). “Do Sounder Banks make Calmer Waters? The Link between Bank Regulations and Capital Flow Waves”. *AEA Papers and Proceedings* 110, pp. 516–522.

Franch, Fabio, Luca Nocciola, and Dawid Żochowski (2019). “Cross-border effects of prudential regulation: evidence from the euro area”. *ECB Working Paper* 2285.

Froot, Kenneth A. and Maurice Obstfeld (1991). “Intrinsic Bubbles: The Case of Stock Prices”. *American Economic Review* 81.5, pp. 1189–1214.

Gadatsch, Niklas, Lukas Mann, and Isabel Schnabel (2018). “A new IV Approach for Estimating the Efficacy of Macroprudential Measures”. *Economics Letters* 168, pp. 107–109.

Galati, Gabriele and Richhild Moessner (2018). “What Do We Know About the Effects of Macroprudential Policy?” *Economica* 85.340, pp. 735–770.

Galí, Jordi (2014). “Monetary Policy and Rational Asset Price Bubbles”. *American Economic Review* 104.3, pp. 721–752.

Galí, Jordi and Luca Gambetti (2015). “The Effects of Monetary Policy on Stock Market Bubbles: Some Evidence”. *American Economic Journal: Macroeconomics* 7.1, pp. 233–257.

Garber, Peter M. (2000). *Famous First Bubbles: The Fundamentals of Early Manias*. Cambridge: MIT Press.

Gauthier, Céline, Alfred Lehar, and Moez Souissi (2012). “Macroprudential Capital Requirements and Systemic Risk”. *Journal of Financial Intermediation* 21.4, pp. 594–618.

Gertler, Mark and Simon Gilchrist (2018). “What Happened: Financial Factors in the Great Recession”. *Journal of Economic Perspectives* 32.3, pp. 3–30.

Gertler, Mark, Nobuhiro Kiyotaki, and Andrea Prestipino (2020). "Banking Panics as Endogenous Disasters and the Welfare Gains from Macroprudential Policy". *AEA Papers and Proceedings* 110, pp. 463–469.

Giannetti, Mariassunta and Yishay Yafeh (2012). "Do Cultural Differences Between Contracting Parties Matter? Evidence from Syndicated Bank Loans". *Management Science* 58.2, pp. 365–383.

Giglio, Stefano, Bryan Kelly, and Seth Pruitt (2016). "Systemic Risk and the Macroeconomy: An Empirical Evaluation". *Journal of Financial Economics* 119.3, pp. 457–471.

Girardi, Giulio and A. Tolga Ergün (2013). "Systemic Risk Measurement: Multivariate GARCH Estimation of CoVaR". *Journal of Banking & Finance* 37.8, pp. 3169–3180.

Gorton, Gary and Andrew Metrick (2012). "Securitized Banking and the Run on Repo". *Journal of Financial Economics* 104.3, pp. 425–451.

Gorton, Gary and Guillermo Ordoñez (2019). "Good Booms, Bad Booms". *Journal of the European Economic Association* 115.6, p. 69.

Granja, João, Christian Leuz, and Raghuram Rajan (2018). "Going the Extra Mile: Distant Lending and Credit Cycles". *NBER Working Paper* 25196.

Granovetter, Mark (2005). "The Impact of Social Structure on Economic Outcomes". *Journal of Economic Perspectives* 19.1, pp. 33–50.

Gray, Dale F. and Andreas A. Jobst (2010). "Systemic CCA – A Model Approach to Systemic Risk". *Working Paper*.

Gromb, Denis and Dimitrios Vayanos (2002). "Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs". *Journal of Financial Economics* 66, pp. 361–407.

Gropp, Reint and André Güttler (2018). "Hidden Gems and Borrowers with Dirty Little Secrets: Investment in Soft Information, Borrower Self-Selection and Competition". *Journal of Banking & Finance* 87 (2018), pp. 26–39.

Gürkaynak, Refet (2008). "Econometric Tests of Asset Price Bubbles: Taking Stock". *Journal of Economic Surveys* 22, pp. 166–186.

Gutierrez, L. (2013). "Speculative Bubbles in Agricultural Commodity Markets". *European Review of Agricultural Economics* 40.2, pp. 217–238.

Halim, Edward, Yohanes Riyanto, and Nilanjan Roy (2019). "Costly Information Acquisition, Social Networks, and Asset Prices: Experimental Evidence". *Journal of Finance* 74.4, pp. 1975–2010.

Han, Bing and Liyan Yang (2013). “Social Networks, Information Acquisition, and Asset Prices”. *Management Science* 59.6, pp. 1444–1457.

Haselmann, Rainer, David Schoenherr, and Vikrant Vig (2018). “Rent Seeking in Elite Networks”. *Journal of Political Economy* 126.4, pp. 1638–1690.

Hautsch, N., J. Schaumburg, and M. Schienle (2015). “Financial Network Systemic Risk Contributions”. *Review of Finance* 19.2, pp. 685–738.

Hellwig, Martin F. (2009). “Systemic Risk in the Financial Sector: An Analysis of the Subprime-Mortgage Financial Crisis”. *De Economist* 157.2, pp. 129–207.

Hollander, Stephan and Arnt Verriest (2016). “Bridging the Gap: The Design of Bank Loan Contracts and Distance”. *Journal of Financial Economics* 119.2, pp. 399–419.

Hong, Harrison G., Jeffrey D. Kubik, and Jeremy C. Stein (2004). “Social Interaction and Stock-Market Participation”. *Journal of Finance* 59.1, pp. 137–163.

— (2005). “Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers”. *Journal of Finance* 60.6, pp. 2801–2824.

Houston, Joel F., Jennifer Itzkowitz, and Andy Naranjo (2017). “Borrowing beyond Borders: Foreign Assets, Lender Choice, and Loan Pricing in the Syndicated Bank Loan Market”. *Journal of Corporate Finance* 42, pp. 315–334.

Huang, Xin, Hao Zhou, and Haibin Zhu (2009). “A Framework for Assessing the Systemic Risk of Major Financial Institutions”. *Journal of Banking & Finance* 33.11, pp. 2036–2049.

Huber, Kilian (2018). “Disentangling the Effects of a Banking Crisis: Evidence from German Firms and Counties”. *American Economic Review* 108.3, pp. 868–898.

Ioannides, Yannis M. and Linda Datcher Loury (2004). “Job Information Networks, Neighborhood Effects, and Inequality”. *Journal of Economic Literature* 42.4, pp. 1056–1093.

Ivković, Zoran and Scott J. Weisbenner (2007). “Information Diffusion Effects in Individual Investors' Common Stock Purchases: Covet thy Neighbors' Investment Choices”. *Review of Financial Studies* 20.4, pp. 1327–1357.

Jackson, Matthew O. (2011). “An Overview of Social Networks and Economic Applications”. In: *Handbook of Social Economics*. Amsterdam [u.a.]: Elsevier, North-Holland, pp. 511–585.

Jayaratne, Jith and Philip E. Strahan (1996). “The Finance-Growth Nexus: Evidence from Bank Branch Deregulation”. *Quarterly Journal of Economics* 111.3, pp. 639–670.

Jiang, Liang, Peter C. B. Phillips, and Jun Yu (2015). "New Methodology for Constructing Real Estate Price Indices Applied to the Singapore Residential Market". *Journal of Banking & Finance* 61, S121–S131.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina (2017). "Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments". *Journal of Political Economy* 125.6, pp. 2126–2177.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2013). "When Credit Bites Back". *Journal of Money, Credit and Banking* 45.s2, pp. 3–28.

— (2015a). "Betting the House". *Journal of International Economics* 96, S2–S18.

— (2015b). "Leveraged Bubbles". *Journal of Monetary Economics* 76, S1–S20.

Kelly, Morgan and Cormac Ó Gráda (2000). "Market Contagion: Evidence from the Panics of 1854 and 1857". *American Economic Review* 90.5, pp. 1110–1124.

Keys, Benjamin J., Tanmoy Mukherjee, Amit Seru, and Vikrant Vig (2010). "Did Securitization Lead to Lax Screening? Evidence from Subprime Loans". *Quarterly Journal of Economics* 125.1, pp. 307–362.

Keys, Benjamin J., Amit Seru, and Vikrant Vig (2012). "Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets". *Review of Financial Studies* 25.7, pp. 2071–2108.

Khwaja, Asim Ijaz and Atif Mian (2005). "Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market". *Quarterly Journal of Economics* 120.4, pp. 1371–1411.

Kim, Jae-Young (2000). "Detection of Change in Persistence of a Linear Time Series". *Journal of Econometrics* 95.1, pp. 97–116.

Kim, Jae-Young and Rosa B. Amador (2002). "Corrigendum to Detection of Change in Persistence of a Linear Time Series". *Journal of Econometrics* 109.2, pp. 389–392.

Kindleberger, Charles P. and Robert Z. Aliber (2005). *Manias, Panics, and Crashes: A History of Financial Crises*. 5th ed. London: Palgrave Macmillan UK.

Kiyotaki, Nobuhiro and John Moore (1997). "Credit Cycles". *Journal of Political Economy* 105.2, pp. 211–248.

— (2005). "Liquidity and Asset Prices". *International Economic Review* 46.2, pp. 317–349.

Koenker, Roger (2005). *Quantile Regression*. Vol. 38. Econometric Society monographs. Cambridge and New York: Cambridge University Press.

Korinek, Anton and Alp Simsek (2016). "Liquidity Trap and Excessive Leverage". *American Economic Review* 106.3, pp. 699–738.

Kramarz, Francis and David Thesmar (2013). "Social Networks in the Boardroom". *Journal of the European Economic Association* 11.4, pp. 780–807.

Krug, Sebastian, Matthias Lengnick, and Hans-Werner Wohltmann (2015). "The Impact of Basel III on Financial (In)stability: An Agent-Based Credit Network Approach". *Quantitative Finance* 15.12, pp. 1917–1932.

Kuchler, Theresa, Yan Li, Lin Peng, Johannes Stroebel, and Dexin Zhou (2020). "Social Proximity to Capital: Implications for Investors and Firms". *NBER Working Paper* 27299.

Kuchler, Theresa, Dominic Russel, and Johannes Stroebel (2020). "The Geographic Spread of COVID-19 Correlates with Structure of Social Networks as Measured by Facebook". *Working Paper*.

Kysucky, Vlado and Lars Norden (2016). "The Benefits of Relationship Lending in a Cross-Country Context: A Meta-Analysis". *Management Science* 62.1, pp. 90–110.

La Porta, Rafael, Florencio López de Silanes, and Andrei Shleifer (2002). "Government ownership of banks". *Journal of Finance* 57.1, pp. 265–301.

Laeven, Luc and Fabián Valencia (2012). "Systemic Banking Crises Database: An Update". *IMF Working Paper* 12/163.

Laeven, Luc and Fabian Valencia (2018). "Systemic Banking Crises Revisited". *IMF Working Paper* 18/206.

LeRoy, Stephen F. and Richard D. Porter (1981). "The Present-Value Relation: Tests Based on Implied Variance Bounds". *Econometrica* 49.3, pp. 555–574.

Levine, Ross (2005). "Finance and Growth: Theory and Evidence". In: *Handbook of Economic Growth*. Ed. by Philippe Aghion and Steven N. Durlauf. Vol. 1. Handbooks in Economics. Amsterdam: Elsevier, pp. 865–934.

Levine, Ross and Sara Zervos (1998). "Stock Markets, Banks, and Economic Growth". *American Economic Review* 88.3, pp. 537–558.

Liberti, José María (2018). "Initiative, Incentives, and Soft Information". *Management Science* 64.8, pp. 3714–3734.

Lieske, Joel A. (1993). "Regional Subcultures of the United States". *Journal of Politics* 55.4, pp. 888–913.

Lin, Mingfeng, Nagpurnanand R. Prabhala, and Siva Viswanathan (2013). "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending". *Management Science* 59.1, pp. 17–35.

López-Espinosa, Germán, Antonio Moreno, Antonio Rubia, and Laura Valderrama (2012). "Short-Term Wholesale Funding and Systemic Risk: A Global CoVaR Approach". *Journal of Banking & Finance* 36.12, pp. 3150–3162.

Mainik, Georg and Eric Schaanning (2012). "On dependence consistency of CoVaR and some other systemic risk measures". *Working Paper*.

Margerit, A., M. Magnus, and B. Mesnard (2017). "The EU Macro-Prudential Policy Framework". *European Parliament Briefing*.

Martin, Philippe and Thomas Philippon (2017). "Inspecting the Mechanism: Leverage and the Great Recession in the Eurozone". *American Economic Review* 107.7, pp. 1904–1937.

Mian, Atif (2006). "Distance Constraints: The Limits of Foreign Lending in Poor Economies". *Journal of Finance* 61.3.

Minsky, Hyman P. (1982). "The Financial-Instability Hypothesis: Capitalist Processes and the Behavior of the Economy". In: *Financial Crises: Theory, History and Policy*. Ed. by Charles P. Kindleberger and J.-P. Laffargue. Cambridge: Cambridge University Press, pp. 13–29.

Monnet, Eric and Miklos Vari (2019). "Liquidity Ratios as Monetary Policy Tools: Some Historical Lessons for Macroprudential Policy, WP/19/176, August 2019". *IMF Working Paper* 176.

Müller, Karsten (2019). "Electoral Cycles in Macroprudential Regulation". *SSRN working paper* 3159086.

Myers, Stweart C. and Nicholas S. Majluf (1984). "Corporate Financing and Investment Decisions when Firms Have Information that Investors Do not Have". *Journal of Financial Economics* 13.2, pp. 187–221.

Nguyen, Bang Dang (2012). "Does the Rolodex Matter? Corporate Elite's Small World and the Effectiveness of Boards of Directors". *Management Science* 58.2, pp. 236–252.

Nguyen, Hoai-Luu Q. (2019). "Are Credit Markets Still Local? Evidence from Bank Branch Closings". *American Economic Journal: Applied Economics* 11.1, pp. 1–32.

Norring, Anni (2019). "Macroprudential Policy Spillovers and International Banking - Taking the Gravity Approach". *ESRB Working Paper Series* 101.

Oh, D. H. and A. J. Patton (2015). "Time-Varying Systemic Risk: Evidence from a Dynamic Copula Model of CDS Spreads". *Working Paper*.

Ongena, Steven, Alexander Popov, and Gregory F. Udell (2013). ""When the Cat's Away the Mice will Play": Does Regulation at Home Affect Bank Risk-Taking Abroad?" *Journal of Financial Economics* 108.3, pp. 727–750.

Ostry, Jonathan D., Atish R. Ghosh, Marcos Chamon, and Mahvash S. Qureshi (2012). "Tools for Managing Financial-Stability Risks from Capital Inflows". *Journal of International Economics* 88.2, pp. 407–421.

Petersen, Mitchell A. and Raghuram G. Rajan (2002). "Does Distance Still Matter? The Information Revolution in Small Business Lending". *Journal of Finance* 57.6, pp. 2533–2570.

Philippon, Thomas and Ariell Reshef (2012). "Wages and Human Capital in the U.S. Finance Industry: 1909–2006". *Quarterly Journal of Economics* 127.4, pp. 1551–1609.

Phillips, Peter C. B. and Shu-Ping Shi (2018). "Financial Bubble Implosion and Reverse Regression". *Econometric Theory* 34.04, pp. 705–753.

Phillips, Peter C. B., Shuping Shi, and Jun Yu (2015a). "Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500". *International Economic Review* 56.4, pp. 1043–1078.

— (2015b). "Testing for Multiple Bubbles: Limit Theory of Real-Time Detectors". *International Economic Review* 56.4, pp. 1079–1134.

Purnanandam, Amiyatosh (2011). "Originate-to-distribute Model and the Subprime Mortgage Crisis". *Review of Financial Studies* 24.6, pp. 1881–1915.

Reinhart, Carmen M. and Kenneth S. Rogoff (2009). *This Time Is Different*. Princeton University Press.

Richter, Björn, Moritz Schularick, and Ilhyock Shim (2019). "The Costs of Macroprudential Policy". *Journal of International Economics* 118, pp. 263–282.

Saadi, Vahid (2020). "Role of the Community Reinvestment Act in Mortgage Supply and the U.S. Housing Boom". *Review of Financial Studies* forthcoming.

Schnabel, Isabel (2004). "The German Twin Crisis of 1931". *Journal of Economic History* 64.3, pp. 822–871.

Schnabel, Isabel and Hyun Song Shin (2004). “Liquidity and Contagion: The Crisis of 1763”. *Journal of the European Economic Association* 2.6, pp. 929–968.

Schularick, Moritz and Alan M. Taylor (2012). “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008”. *American Economic Review* 102.2, pp. 1029–1061.

Segoviano, Miguel A. and Charles Goodhart (2009). “Banking Stability Measures”. *IMF Working Paper* 09/4.

Shiller, Robert J. (1981). “Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?” *American Economic Review* 71.3, pp. 421–436.

— (2000). *Irrational Exuberance*. Princeton, NJ: Princeton University Press.

Shin, Hyun Song (2008). “Risk and Liquidity in a System Context”. *Journal of Financial Intermediation* 17.3, pp. 315–329.

Shleifer, Andrei and Robert Vishny (1992). “Liquidation Values and Debt Capacity: A Market Equilibrium Approach”. *Journal of Finance* 47.4, pp. 1343–1366.

— (1997). “The Limits of Arbitrage”. *Journal of Finance* 52.1, p. 35.

— (2011). “Fire Sales in Finance and Macroeconomics”. *Journal of Economic Perspectives* 25.1, pp. 29–48.

Takáts, Előd and Judit Temesvary (2019). “How does the Interaction of Macroprudential and Monetary Policies Affect Cross-Border Bank Lending?” *FEDS Working Paper* 045.

Uchida, Hirofumi, Gregory F. Udell, and Nobuyoshi Yamori (2012). “Loan Officers and Relationship Lending to SMEs”. *Journal of Financial Intermediation* 21.1, pp. 97–122.

van Bekkum, Sjoerd, Marc Gabarro, Rustom M. Irani, and José-Luis Peydró (2019). “Take It to the Limit? The Effects of Household Leverage Caps”. *SSRN working paper* 3284670.

Vandenbussche, Jérôme, Ursula Vogel, and Enrica Detragiache (2015). “Macroprudential Policies and Housing Prices: A New Database and Empirical Evidence for Central, Eastern, and Southeastern Europe”. *Journal of Money, Credit and Banking* 47.1, pp. 343–377.

Wang, Yihui and Han Xia (2014). “Do Lenders Still Monitor When They Can Securitize Loans?” *Review of Financial Studies* 27.8, pp. 2354–2391.

West, Kenneth D. (1987). “A Specification Test for Speculative Bubbles”. *Quarterly Journal of Economics* 102.3, pp. 553–580.

Wong, Tak-chuen, Tom Fong, Ka-fai Li, and Henry Choi (2011). "Loan-to-Value Ratio as a Macro-Prudential Tool: Hong Kong's Experience and Cross-Country Evidence". *SSRN working paper* 1768546.

Wurgler, Jeffrey (2000). "Financial Markets and the Allocation of Capital". *Journal of Financial Economics* 58.1-2, pp. 187–214.

Xiong, Wei (2001). "Convergence Trading with Wealth Effects: An Amplification Mechanism in Financial Markets". *Journal of Financial Economics* 62, pp. 247–292.