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Dominik Fabian Damast

aus Bonn

Bonn

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Dekan:	Prof. Dr. Martin Böse
Erstreferent:	Prof. Dr. Farzad Saidi
Zweitreferent:	Prof. Dr. Jing Zeng
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Introduction

Insurance companies are among the largest groups of financial intermediaries. Their products offer households protection against various risks to life and property, hence being an integral part of households' risk management. As most households have one or more insurance policies, insurance companies collect large amounts of premiums, which they invest in financial assets such as bonds, stocks, and asset-backed securities.

These asset holdings connect insurance companies directly with various sectors of financial markets. For example, insurance companies are among the largest investors in banks' corporate bond debt, creating a direct asset-liability link that could become a contagion channel of financial distress in crisis times. In general, insurers' security holdings expose them to financial risks and give them a pivotal role in the financial system. As insurers' liabilities consist of long-term promises to policyholders, understanding insurers' investment behavior and their role in transmitting aggregate shocks is crucial for households' consumption decisions and, thereby, the financial system's stability. This thesis consists of three self-contained papers investigating different aspects of insurance companies' role in financial markets: insurers' investments in other financial institutions, the impact of monetary policy on insurance markets, and the spillovers of insurers' and other institutional investors' corporate bond demand to loan markets.

Chapter 1 studies the interlinkage of insurance companies with other financial institutions, particularly banks, via the corporate bond market. This study is motivated by the fact that financial institutions rely on long-term bond debt as a funding source, and insurance companies hold a large chunk of this debt, representing a significant portion of their balance sheet. Using detailed regulatory data on U.S. insurance companies' corporate bond investments, I first document that small insurers overinvest in bonds of financial institutions ("finance bonds") relative to a market portfolio. In contrast, large insurers underinvest relative to the market. Other bond characteristics like maturity or yield spreads cannot explain this pattern. Second, finance bonds carry the lowest idiosyncratic risk among all corporate bonds, even when controlling for bailout expectations related to financial institutions. Combining these facts, I hypothesize that the origin of the negative size-investment relationship for finance bonds lies in insurers' incentive to diversify their corporate bond portfolio. To test this hypothesis, I examine insurers' investment behavior around a regulatory reform of exchange-traded funds investing only in bonds ("bond ETFs") in 2017 that extended insurers' access to these instruments. I show that small insurers' overinvestment decreased after this reform, and their investment shifted to bond ETFs. I explain these results with a model where capital regulation incentivizes insurers to diversify, but high transaction costs in corporate bond markets make diversification costly. Acquiring bonds of financial institutions solves this trade-off of transaction and regulatory costs for constrained insurers. Finally, I empirically test further predictions of the model. More specifically, I show a positive association between the idiosyncratic volatility of insurers' liabilities and their finance bond investments and a negative association between insurers' size and the degree of intermediated diversification. Overall, this study provides evidence that insurers use finance bonds as a tool for diversification due to the issuers' financial intermediation function. My findings suggest that regulators should be cautious about this relationship. As of today, small insurers still represent a significant fraction of insurance policies, which constitutes an integral part of household wealth. If financial institutions carry other hidden risks, like in the 2008 crisis, a substantial portion of insurance markets is exposed.

Chapter 2 (joint work with Christian Kubitza and Jakob Ahm Sørensen) examines how monetary policy affects insurance markets, transmitting to local housing and mortgage markets. In this study, we focus on homeowners insurance as it is one of the most commonly held insurance products, e.g., because it is mandatory for obtaining a mortgage in the U.S. In a stylized model, we show that monetary policy incentivizes insurers to increase prices in the presence of regulatory frictions. As insurers must maintain sufficient regulatory capital, increasing interest rates, which depress the market value of insurers' legacy assets, tighten regulatory frictions. In response, insurers raise prices to bolster their regulatory capital. Taking the model's predictions to the data, we exploit detailed data on regulatory filings of homeowners insurance companies, which we merge with security-level information on insurers' asset holdings. The data allow us to observe individual price changes of every U.S. insurer in the homeowners insurance market from 2009 to 2019. Because insurers' security holdings have a long duration, we identify monetary policy surprises using high-frequency changes in the 10-year Treasury yield. We begin by documenting that insurers increase prices in response to contractionary monetary policy surprises. This effect is robust to a large set of controls, different sample periods, and various methodologies to measure monetary policy surprises. The positive response of insurance prices to higher interest rates suggests the presence of frictions in insurance price setting. To reveal these frictions, we zoom in on the impact of monetary policy surprises on insurers' balance sheets. We find that a contractionary monetary policy shock negatively affects insurers' investment income – an essential determinant of insurance prices. Disentangling the different components of insurers' investment income, we find that primarily insurers' holdings of stocks and high-yield bonds, which are held at mark-to-market and, to a lesser extent, realized losses on sales of investment-grade bonds, which are held at historical costs, drive the negative impact of monetary policy hikes on investment income. We show that each dollar of investment income translates almost one-to-one to insurers' regulatory capital; hence, contractionary monetary policy tightens insurers' regulatory constraints. Combining the previous findings, we show that regulatory frictions, tightened by the response of insurers' investment income, are the key channel through which monetary policy affects insurance prices. First, we document that more regulatory-constrained insurers increase prices relatively more after monetary policy hikes. Second, insurers' regulatory constraints interact with the sensitivity of their investment income to monetary policy. In particular, constrained insurers with a long asset duration and a larger share of mark-to-market assets are most responsive to monetary policy surprises. These insurers face particularly strong regulatory incentives to bolster their regulatory capital and, to achieve that, substantially increase insurance prices. Finally, we study the implications of our findings for the real economy. As premiums for homeowners insurance constitute a substantial part of the cost of housing, we analyze how monetary policy shocks affect local housing and mortgage markets. We find that an interest rate hike leads to a larger decline in home values and mortgage demand in counties whose local insurance companies are more sensitive to interest rate changes. The effect is particularly pronounced for counties prone to natural disasters, i.e., where insurance policies are relatively more costly. Our findings establish a new monetary policy transmission channel to the real economy. By raising insurance prices after interest rate hikes, the insurance sector exacerbates the effect of monetary policy shocks by tightening households' budget constraints and, therefore, cooling the economy.

Chapter 3 (joint work with Marcel Brambeer) analyzes how institutional investors' corporate bond demand affects loan market outcomes. Insurance companies are, alongside mutual funds, the most important institutional investors in corporate bond markets, substantially impacting asset prices. Differences in insurers' and mutual funds' liability structures suggest differential bond demand changes to aggregate shocks. As firms receive debt funding from different competing sources, i.e., bond investors and banks, these bond demand changes potentially spill over to firms' loan demand. This study addresses this question regarding investors' reaction to monetary policy. Our analysis consists of two steps. In the first step, we build a panel tracking insurance companies' and mutual funds' security-level investments in corporate bonds. The panel structure of our data allows us to employ granular fixed effects absorbing potential effects of monetary policy on bond supply. We show that an interest rate hike lowers mutual funds' bond demand more strongly than insurers' bond demand. This decrease is particularly pronounced for bonds with medium maturity and high-yield bonds. We analyze how these bond demand changes affect loan markets in the second step. We construct a dataset covering all borrowing relationships of U.S. firms whose bonds we analyzed in the first step. We face two challenges in identifying bond demand spillovers to firms' loan demand. First, we need to control for potential changes in lenders' loan supply. The panel data structure allows us to include lender-time fixed effects absorbing any borrower-invariant changes in loan supply. Second, we must measure exogenous changes in the demand for firms' bonds. We address this issue by constructing a new variable that combines the pre-shock exposure of firms' bonds to insurers with the differential change in insurers' and mutual funds' engagement in the bond market. We find that firms with a relatively higher demand for their bonds after a contractionary monetary policy surprise are less likely to take out a loan. In particular, risky firms and firms with a medium average bond maturity adjust their loan demand. Our results emphasize the importance of firms' investor composition for monetary policy transmission.

Chapter 1

Insurers Use Banks for Portfolio Diversification

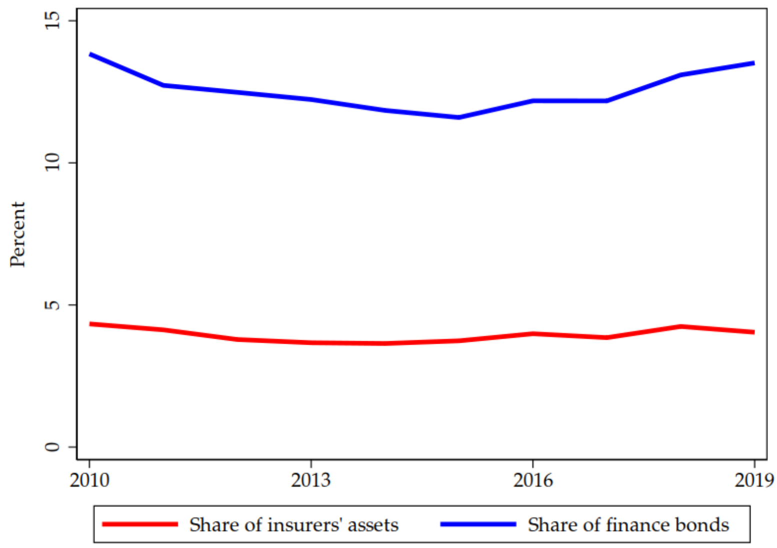
1.1 Introduction

The financial sector is the largest issuer of corporate bonds. From 2010 to 2019, financial institutions accounted for over a third of the total issuance of $20 trillion, according to Mergent FISD. Both non-depository institutions for whom corporate bonds are already a significant funding source and depository institutions who increasingly rely on (long-term) bonds as non-deposit funding source contribute to these numbers. On the investor side, U.S. insurance companies pose one of the largest investor groups in corporate bond markets in general and for financial institutions (including other insurers) in particular.

The importance of this connection is sizeable for both sides. From 2010 to 2019, U.S. insurance companies always held around 12 percent of the financial sector's bond debt (see Figure 1.1.1). On the investors' side, these holdings made up almost five percent of insurers' total assets, creating a significant exposure for insurance companies. However, despite this deep interconnectedness of insurers with the remainder of the financial sector, we know little about its drivers. This paper aims to fill this gap.

In this paper, I exploit detailed regulatory data on U.S. insurers' corporate bond investments to examine insurers' use of bonds issued by the financial sector ("finance bonds"). The security-level data on insurers' fixed income portfolios allows me to identify whether a corporate bond was issued by a financial institution or a non-financial entity. I begin by benchmarking insurers' investments in finance bonds vis-à-vis other industry sectors and document that finance bonds have lower idiosyncratic risk than their non-finance counterparts. Subsequently, I investigate how a change in the regulatory treatment of exchange-traded funds investing only in bonds ("bond ETFs") in 2017 impacted insurers' investment in finance bonds. Then, I present a simple model of insurers' portfolio choice in corporate bond markets. The model's mechanism is rooted in the spirit of Diamond (1984). Analogous to Diamond (1984), where a financial intermediary creates value for their investors by minimizing monitoring cost through diversification, my model features a diversified financial intermediary whose bonds insurers use as a tool to avoid transaction costs associated with corporate bond acquisitions. The model fulfills two purposes. First, it rationalizes the previous observations. Second, I derive further predictions that I can test with the data.

Figure 1.1.1. Reciprocal importance of insurers' finance bond investments



Notes: This figure shows the share of insurers' total assets invested in finance bonds (red graph) and the share of the financial sector's corporate bond debt held by US insurance companies (blue graph) between 2010 and 2019. Sources: NAIC Regulatory Filings, Mergent FISD and author's calculations.

Overall, I provide evidence that insurers – a large group of institutional investors – use finance bonds as a diversification tool for their corporate bond portfolio. As financial institutions diversify idiosyncratic risk away, their bonds implicitly offer a diversification function. Insurance regulation induces insurers to minimize idiosyncratic risk and insurers' urge to do so depends on the volatility of their liability side, i.e., the liability risk (see Knox and Sørensen (2024)). Hence, insurers' use of finance bonds depends on the volatility of their liabilities. This paper exploits various sources of heterogeneity in insurers' liability risk, e.g., insurers' size, and changes in the regulatory landscape to create empirical evidence that investors value financial intermediaries' role in managing idiosyncratic risk.

Testing empirically whether investors see financial institutions as a means to diversify their portfolio faces several key challenges. First, one has to disentangle the diversification function from other purposes related to investing in those companies. For example, households not only hold deposits with banks because these specialize in giving out diversified loan portfolios but also because bank accounts grant depositors access to other financial services and safe storage of funds. Second, there is a plethora of retail products like ETFs that offer cheap access to diversified portfolios. Lastly, investors follow different investment strategies based on parameters that are either hard to estimate, e.g., risk-aversion for retail investors, or fixed by regulation, e.g., indices.

Focussing on insurers as a particular group of investors allows me to overcome these challenges. First, insurance companies' primary motive for investing in corporate bonds is to generate investment returns on the premiums collected in their underwriting business.[1] For insurers, corporate bond investments do not serve other purposes like safe storage of funds as they have access to other, cheaper, and more liquid instruments like U.S. Treasuries. Second, until 2017, insurance companies had limited access to bond ETFs. The 2017 bond ETF reform extended insurers' access to bond ETFs and allowed small insurers to invest in a low-cost, diversified portfolio of corporate bonds. Third, within the asset class of corporate bonds, I can control for differences in insurers' investment strategies with information on bond issues' liquidity, maturity, credit risk, and various other properties.

As a first step, I present four novel stylized facts about insurers' corporate bond portfolios and finance bonds. First, the number of securities in insurers' corporate bond portfolios grows with size. While large insurers hold portfolios of several hundreds of bonds, most of the smaller insurers focus on a limited number of securities. However, the bonds held are more important relative to their asset size. Second, there is a negative size-investment relationship for finance bonds, i.e., the portfolio share of finance bonds decreases with insurers' size. The size-investment relationship is unique among all industry sectors in magnitude and significance. In the third fact, I show that known mechanisms such as reaching for yield (Becker and Ivashina, 2015), liquidity, and others do not drive the results. The last fact unveils a new perspective on finance bonds motivated by financial institutions' diversification function. More specifically, bonds issued by financial institutions exhibit the lowest idiosyncratic risk among all corporate bonds and, thus, present a viable tool for diversification.

Subsequently, I argue that diversification motives drive insurers' investment behavior. For this, I exploit the 2017 reform that changed bond ETFs' accounting and valuation rules for insurers. Before the reform, investments in bond ETFs were accounted for and valued like equity investments, which have larger capital requirements than bonds. After the reform, bond ETFs received bond-like treatment, which gave insurers access to a diversified portfolio of bonds at a lower cost. Suggestive evidence shows that small insurers started to invest in bond ETFs after the reform. Then, to ensure better identification, I follow the approach from

1. Knox and Sørensen (2024) show that insurers generate investment returns to sustain lower prices on the insurance policies and, thereby, price more competitively.

Becker and Ivashina (2015) and Becker, Opp, and Saidi (2022) to show that the overall share of an issue acquired by small insurers decreased after the reform.

I rationalize the previous results in a simple model of insurers' portfolio choice in corporate bond markets. In the model, an insurer with volatile liabilities builds a portfolio of risky assets. Additionally, the insurer can buy a bond issued by a bank holding a diversified portfolio of risky assets. The model features two frictions. First, the insurer incurs a fixed transaction fee for each asset acquired. This transaction fee penalizes the diversification efforts of small portfolios. Second, insurers are subject to risk-based capital regulation, which makes volatile portfolios costly.

These two frictions introduce a tradeoff in the insurer's optimization problem, and the insurer's size determines the relative importance of these frictions. A diversified portfolio of risky assets leads to higher transaction cost because of the increased number of trades required. On the other hand, a diversified portfolio has lower volatility and reduces insurers' expected regulatory cost. In this setup, the bank offers access to a diversified bond portfolio that avoids high transaction cost but comes at the cost of lower returns on the bank bonds. The tradeoff is more severe for small insurers as the transaction cost constraint is more stringent for them. Hence, small insurers overweight finance bonds relative to large insurers.

Besides this main result, I derive three empirical predictions from the model that align with the initial hypothesis that insurers view finance bonds as a diversification tool. First, a shift in the transaction cost - like the one induced by the bond ETF reform - changes the relationship between size and insurers' finance bond investments. Second, a positive relationship exists between the volatility of insurers' liabilities and their finance bond investments. Third, the degree of diversification of the financial institution issuing the bond determines the amount of finance bonds in insurers' portfolios.

The bond ETF reform has been an empirical test of the first prediction. To test the second prediction, that is, insurers' liability risk and investments in finance bonds are positively related, I exploit heterogeneity in insurers' organizational characteristics and underwriting properties, determining the volatility of insurers' liability side. First, insurers' risk on the liability side depends on whether insurers belong to an insurance group and whether insurers are organized as a stock company or a mutual company. Insurance groups serve as internal capital markets and allow better risk sharing (see Ge (2022), Oh, Sen, and Tenekedjieva (2023), Koijen and Yogo (2016)); stock insurers have better access to external capital, while mutual insurers are constrained. I observe that the relationship between size and finance bond investments is weaker for insurers who are part of an insurance group and for stock insurers. Second, I use heterogeneity in spatial and business properties of insurers' underwriting business, which is the primary source of the volatility of their liabilities.[2] The previous literature on insurers' liabilities, such as Che and Liebenberg (2017), Elango, Ma, and Pope (2008), Liebenberg and Sommer (2008), and Hoyt and Trieschmann (1991), offers several proxies, like the degree of spatial diversification and the degree of business diversification. I find that spatially more concentrated insurers and insurers with a narrower business focus invest more in finance bonds. This relationship becomes weaker when the insurers are larger. In a third test, I exploit regulatory constraints of property and casualty (P&C) insurers across U.S. states that limit their ability to adjust prices. P&C insurers must file price changes with local regulatory authorities. The local regulators then decide whether to accept, change, or deny the request. Oh, Sen, and Tenekedjieva (2023) show for the context of homeowners insurance that P&C insurers are subject to significant constraints in price setting across U.S. states. As a result, there is considerable variation in insurers' ability to flexibly adjust prices according to actuarial considerations (plus some markups). This variation is significantly related to the share of finance bonds in the corporate bond portfolio, and the interaction term with insurers' size goes in the opposite direction. However, this test offers less statistical significance due to data limitations.

To test the third prediction, that is, the degree of diversification of the financial institution issuing the bond determines the amount of finance bonds in insurers' portfolios, I leverage transaction-level data from the syndicated loan market to measure financial institutions' degree of diversification. I classify a financial institution as diversified if it lends significant funds in the syndicated loan market. Consistent with the model's predictions, small insurers invest relatively more in finance bonds issued by lenders, which are highly active in the syndicated loan market. In contrast, large insurers hold bonds of more specialized financial institutions. Although these results are partially statistically insignificant, they point to insurers viewing finance bonds as a diversification tool.

Finally, I provide evidence that rules out other potential explanations. First, I examine transaction cost in corporate bond markets and find that the most liquid finance bonds are similar in liquidity to the most liquid bonds of other industry sectors. Second, the relationship is not driven by the OTC nature of U.S. corporate bond markets where large dealers serve as market makers. Insurers must have a relationship with a (large) dealer bank to access corporate bond markets. Small insurers might have to buy bonds from the company directly or a related

2. Warren Buffett, in his 2002 letter to the shareholders of Berkshire Hathaway, made the importance of the underwriting business clear: "To begin with, the float is money we hold but don't own. In an insurance operation, float arises because premiums are received before losses are paid, an interval that sometimes extends over many years.[...] Historically, Berkshire has obtained its float at a very low cost. Indeed, our cost has been less than zero in many years; that is, we've actually been paid for holding other people's money. In 2001, however, our cost was terrible, coming in at 12.8%, about half of which was attributable to World Trade Center losses. Back in 1983-84, we had years that were even worse. There's nothing automatic about cheap float." (Buffett (2002), p. 7)

subsidiary that provides the dealer services to maintain a good relationship or as an entry ticket to corporate bond markets. An analysis of insurers' transaction data in which I can observe the transaction's counterparty does not find evidence in favor of this explanation. Small and large insurers buy with equal probability a bond of an issuer who also serves as the counterparty of the trade.

Related literature. This paper relates to several strands of the literature. First, it relates to the research on the role of nonbanks in financial markets. Previous literature has explained the rise of nonbank presence in credit markets with technological advances (Buchak, Matvos, Piskorski, and Seru (2018), Fuster, Plosser, Schnabl, and Vickery (2019)), regulation (Ordoñez (2018), Irani, Iyer, Meisenzahl, and Peydró (2021), Roure, Pelizzon, and Thakor (2022), Chen, Lee, Neuhann, and Saidi (2023)), heterogeneous exposure to monetary policy (Chen, Ren, and Zha (2018), Nelson, Pinter, and Theodoridis (2018), Elliott, Meisenzahl, Peydro, and Turner (2019), Elliott, Meisenzahl, and Peydro (2023)), and liquidity transformation (Moreira and Savov (2017)). Almost all previous studies have in common that the results imply banks and nonbanks are substitutes (in credit markets). Only Chen, Lee, et al. (2023) point out that banks and nonbanks can take complementary roles in credit markets. I add to this literature by showing that nonbanks and banks are complements in the corporate bond market as insurers use corporate bonds issued by banks (and other financial institutions) as a tool to diversify their bond portfolio.

Second, this paper relates to the growing literature on the role of insurers in financial markets. A significant part of the literature has examined the price impact of insurers' bond demand (Ellul, Jotikasthira, and Lundblad (2011), Fache Rousová and Giuzio (2019), Chodorow-Reich, Ghent, and Haddad (2021)) and the associated real effects (Kubitza (2023), Massa and Zhang (2021), Manconi, Massa, and Zhang (2016), Liu, Rossi, and Yun (2021)). Moreover, Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner (2022) and Kubitza, Grochola, and Gründl (2023) show that certain contractual features of life insurance products increase systemic risk and the probability of fire sales. Girardi, Hanley, Nikolova, Pelizzon, and Sherman (2021) draw attention to the overlap of insurers' portfolios, which bears the risk of causing fire sale dynamics in times of financial market stress.

The three most closely related papers from this strand of literature are Garmaise and Moskowitz (2009), Sastry (2022), and Bosshardt, Kakhbod, and Saidi (2022), which study various interactions between banks and insurance companies. Garmaise and Moskowitz (2009) and Sastry (2022) prove that insurance contracts affect the loan approval decisions of banks. Bosshardt, Kakhbod, and Saidi (2022) have exploited the heterogeneity in banks' funding dependence on insurance companies to identify exogenous changes in banks' Liquidity Coverage Ratio (LCR). This paper contributes to this literature by examining the corporate bond market transmission channel between insurance companies and other financial institutions. It broadens the view from banks to other financial institutions and explains the motivation of insurers to create such an interlinkage.

Third, this paper contributes to the general insurance literature, which explores the functioning of the insurance industry and insurance companies' operations. This paper adds to our understanding of insurers' investment choices (Sen (2022), Becker, Opp, and Saidi (2022), Knox and Sørensen (2024), Ellul, Jotikasthira, Lundblad, and Wang (2015)).[3] The two most closely related papers from this field are Becker and Ivashina (2015) and Ge and Weisbach (2021). Becker and Ivashina (2015) find that insurance companies generally invest in high-quality bonds, but insurers are reaching for yield within the risk buckets defined by the regulator. Ge and Weisbach (2021) show that smaller insurers prefer to buy more liquid bonds. I add to the determinants of insurers' investment behavior by showing that insurers' investment strategy is also affected by the qualitative properties of the issuer of the asset and not only the bond itself.

1.2 Insurers and Finance Bonds

In this section, I first describe the main data and variables; then, I present four novel stylized facts. First, small insurers invest in few securities each representing a significant fraction of their asset side while large insurers hold a large number of securities with every security making up only a small fraction of total assets. Second, there is a negative relationship between insurers' size and the portfolio share of finance bonds which is unique among all industry sectors because small insurers hold a majority of their corporate bond investments in finance bonds while large insurers hold multiple industry sectors. Third, potential drivers like "reaching for yield" or a preference for liquidity fail to explain the first two facts. Lastly, finance bonds have lower idiosyncratic risk than their non-finance counterparts.

1.2.1 Data Construction and Summary Statistics

The main data are insurance companies' end-of-year corporate bond portfolios. The NAIC requires insurance companies to report their entire security holdings at the end of each year. I access the corporate bond holdings in Schedule D Part 1, which gives me detailed information on insurers' securities holdings. More specifically, I observe the amount held in each bond, the effective yield to maturity at the time of acquisition, the acquisition date, and other. From Mergent FISD, I match

3. Related strands in this literature have studied drivers of insurers' price setting (e.g., Froot and O'Connell (1999), Froot (2001), Oh, Sen, and Tenekedjieva (2023), Knox and Sørensen (2024), Ge (2022), Giambona, Kumar, and Phillips (2021), Tang (2022)), insurers' role in the 2008 crisis (e.g., Koijen and Yogo (2015), Bhutta and Keys (2021), McDonald and Paulson (2015)), insurers' risk management (e.g., Sen and Sharma (2020), Foley-Fisher, Narajabad, and Verani (2020)), and insurance regulation (e.g., Tenekedjieva (2021), Leverty and Grace (2018)).

issue-level information by using the bonds' CUSIP. In particular, I get information on the size of the bond issue, the industry code of the issuer, a bond's end-of-year credit rating, maturity date, and other.

Table 1.2.1. Summary statistics for the insurer-year-level sample

	N	Mean	SD	1st	25th	Median	75th	99th
Full sample								
Assets (mn $)	551,670	3,123.72	18,377.94	2.52	30.39	117.51	541.02	70,614.38
ROE	549,108	4.72	31.22	-160.25	-0.24	5.47	15.16	98.66
RBC ratio	534,597	34.85	70.36	1.45	6.10	9.78	18.94	384.30
Portfolio HHI	551,670	34.32	21.31	14.12	21.07	27.11	37.80	100.00
Share	551,670	4.76	11.86	0.00	0.00	0.00	3.28	56.64
Finance	26,270	35.98	22.02	0.00	21.54	33.33	45.95	100.00
Sector rating	551,670	15.55	1.80	11.86	14.34	15.55	16.72	20.11
P&C insurers								
	N	Mean	SD	1st	25th	Median	75th	99th
Assets (mn $)	418,656	956.40	6,047.06	2.66	27.71	95.77	360.66	17,182.32
ROE	417,081	4.77	29.68	-147.38	0.06	5.21	14.61	94.14
RBC ratio	403,662	39.91	77.46	1.45	5.76	9.77	21.22	384.30
Portfolio HHI	418,656	36.78	21.85	14.70	23.02	29.15	40.57	100.00
Share	418,656	4.76	12.35	0.00	0.00	0.00	2.92	59.56
Finance	19,936	38.03	22.61	0.00	23.91	35.89	48.28	100.00
Sector rating	418,656	15.55	1.80	11.86	14.34	15.55	16.72	20.11
Life insurers								
	N	Mean	SD	1st	25th	Median	75th	99th
Assets (mn $)	133,014	9,945.24	34,991.36	2.07	48.84	393.14	3,210.00	204,781.28
ROE	132,027	4.56	35.66	-160.25	-2.09	6.35	17.44	98.66
RBC ratio	130,935	19.27	37.36	2.10	7.03	9.79	15.28	216.82
Portfolio HHI	133,014	26.59	17.34	14.12	17.50	20.77	27.22	100.00
Share	133,014	4.76	10.19	0.00	0.00	0.62	4.44	45.83
Finance	6,334	29.51	18.62	0.00	17.87	25.84	36.28	100.00
Sector rating	133,014	15.54	1.80	11.65	14.32	15.55	16.70	20.11

Notes: This table shows the summary statistics for the main insurer-year panel. *Assets (mn $)* are insurer i's total assets at the end of year t. *Asset growth* is the growth of insurer i's total assets from year $t-1$ to t. *ROE* is insurer i's return on equity in year t. *RBC ratio* is insurer i's risk-based capital ratio at the end of year t. *Portfolio HHI* is the Herfindahl-Hirschman index across industry investments of insurer i's corporate bond portfolio. *Share* is insurer i's share of the corporate bond portfolio invested into bonds from NAICS sector s at the end of year t. *Finance* is insurer i's share of the corporate bond portfolio invested into bond from NAICS sector 52 at the end of year t. *Rating* is the average credit rating of the industry sector s's bonds held by the insurer i at the end of year t.

With this data, I construct an insurer-sector-time panel which tracks insurers' corporate bond portfolio allocation across industry sectors each year. To identify industries, I rely on the two-digit industry sector definition from the North American Industrial Classification System (NAICS). As is standard with this industry classification, some industry codes are combined to form a single industry, e.g., the codes 31 to 33 are combined into 31-33 "Manufacturing". For each insurer, I calculate the share of the corporate bond portfolio allocated to industry sectors each year. To calculate the portfolio share, I use the par value of bonds as this proxies best for the bond demand. Moreover, I count the number of securities held by an insurer in each industry sector and compute the average effective yield reported of the securities held in this industry sector (weighted by par value).

I supplement this data with information on insurers' assets and liabilities that they have to report alongside the security holdings. In particular, I consider the variables *Total assets*, *Risk-based capital (RBC) ratio*, *Return on Equity (ROE)*, and *Leverage*. I add a measure of insurers' portfolio concentration across industry sectors. To measure the concentration of an insurer's portfolio, I calculate the Herfindhal-Hirschman index (*Portfolio HHI*) across sector holdings. Moreover, I add the average credit rating of bonds in an industry sector. All financial variables are winsorized at the 1% and 99% levels.

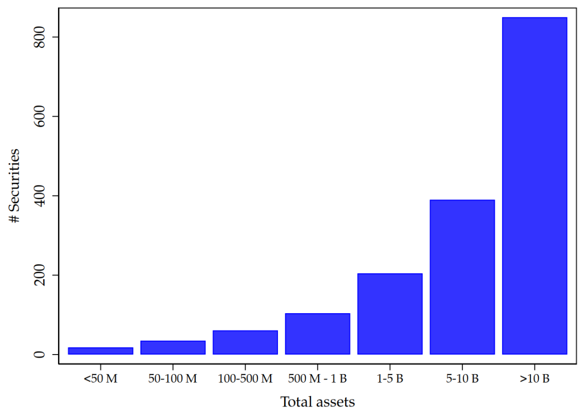
Table 1.2.1 shows summary statistics. The sample period ranges from 2010 to 2019. On average, I have more than 2,600 insurers a year, no less than 2,594, and no more than 2,681 (see Table 1.E.1). There are substantially more property and casualty (P&C) insurers than life insurers. The median insurer is only around $115 million in total assets. Furthermore, the summary statistics show that some insurers invest only in a single industry sector, and a large portion of those invests only in finance bonds. Finance bonds play an important role in insurers' portfolios, as the average share for finance bonds is approximately 36 percent. The average share of any other industry only amounts to less than 5 percent.

1.2.2 Stylized Facts

Insurance companies are one of the largest investor groups in the corporate bond market. There is, however, large heterogeneity in the portfolio choices of insurance companies. Most insurance companies invest only in a limited number of securities, firms, and industry sectors.[4] At first, I look at the cross-section of insurance companies with regard to size. I split insurance companies into seven different buckets according to their size measured in total assets: insurers with assets below $50 million, between $50 and $100 million, $100 and $500 million, $500 million and $1 billion, $1 and $5 billion, $5 and $10 billion, and above $10 billion. Figure 1.2.1 shows the median number of securities held by insurers in each of the seven size buckets. In particular small insurers have portfolios with a small number of securities. The majority of those build their portfolios on 20 securities or less. Even most insurers with total assets between $50 million and $100 million have portfolios with less than 50 securities. In contrast, the largest insurers maintain broad portfolios with over 800 securities.

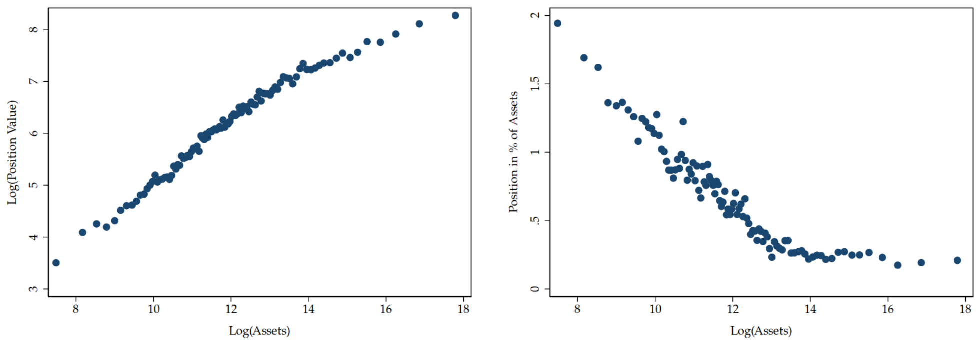
4. Kubitza (2023) shows that most insurers have a fixed set of companies they build on their portfolio. This persistence allows Kubitza (2023) to identify the transmission of financial shocks on insurers' underwriting activity to firms' debt structure and investment.

Figure 1.2.1. Insurers' portfolio width across size



Notes: This figure shows the median number of corporate bond securities invested by insurers of different sizes.

Figure 1.2.2. Portfolio position sizes across insurers' size



(a) Absolute position size

(b) Relative position size

Notes: This figure shows binned scatter plots for (a) the average absolute and (b) average relative position investments across insurers' size. Panel (a) plots the natural logarithm of the par value of an individual position and panel (b) plots the par value relative to total assets. Each plot controls for *RBC ratio* and *Leverage*.

Looking at the individual security positions, small insurers' exposure to a few corporate bond securities becomes clearer. First, on average, the absolute amount invested in a single security increases with insurers' size (see panel (a) of Figure 1.2.2). However, panel (b) of Figure 1.2.2 shows that the amount invested in a single security relative to the insurer's size decreases with the insurers' size. For the smallest insurers, each position makes up more than 1 percent of their asset side, while for the largest insurers, it makes up less than 0.2 percent. Put differently, small insurers focus on a few corporate bond securities where each position individually constitutes a significant part of their asset side. Large insurers maintain large portfolios with many securities where each position individually constitutes only a small part of their asset side. This observation summarizes the first fact.

Fact 1. Small insurers' corporate bond portfolios consist of few securities each representing a significant part of total assets. Large insurers maintain broad corporate bond portfolios where each security accounts only for a small fraction of total assets.

The first fact shows that small insurance companies have large exposure to a small number of securities while large companies build a balanced portfolio. Next, I take a closer look at the issuers of these securities. More specifically, I examine the industry of the issuers. Panel (a) of Figure 1.2.3 shows for each industry sector the share of insurers that invest a part of their portfolio in securities issued by companies of this sector. The sectors "Manufacturing" (31-33) and "Finance and Insurance" (52) are the most prominent. The other sectors are represented only in a fraction of insurers' portfolios; even bonds from capital-intensive sectors like "Mining" are in only about 70 percent of insurers' portfolios. However, almost all insurers invest in bonds of companies from "Finance" and "Manufacturing." Bonds from financial companies are in nearly 95 percent of insurers' portfolios. Zooming in on the finance sector holdings, I find that small insurers invest much more in finance bonds than large insurers. Panel (b) of Figure 1.2.3 shows the average portfolio share of finance bonds relative to the market portfolio share across the seven size buckets.[5] Small insurers overweight the market portfolio by almost 10 percentage points, while large insurers underweight it by almost 10 percentage points. As the market portfolio share over the entire sample period was never lower than 30 percent (see Figure 1.D.2), this means that small insurers invest almost 40 percent of their corporate bond portfolio in finance bonds. Moreover, there is a negative relationship between size and the reliance on finance bonds.

To confirm the conjecture given by Figure 1.2.3, I regress insurers' portfolio shares, $Share_{ist}$, on a set of interactions of industry dummies with insurers' size $Log(Assets)_{it}$,

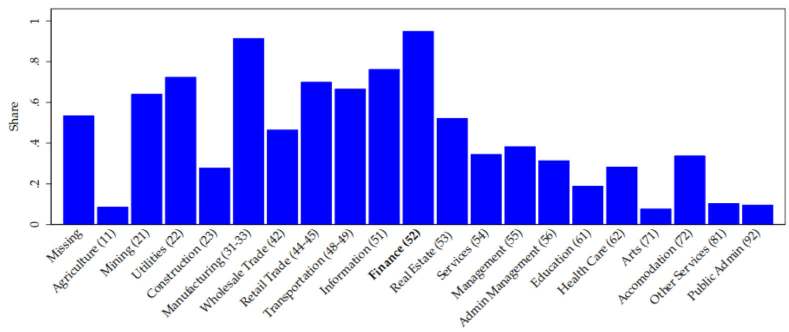
$$\begin{aligned}\text{Share}_{ist} = {} & \sum_s \beta_s\, \mathbb{1}\{\text{Industry} = s\} \times \text{Log(Assets)}_{it} \\ & + \beta_{Missing}\, \text{Log(Assets)}_{it} + \gamma \boldsymbol{X}_{it} + u_{is} + v_t + \varepsilon_{it}.\end{aligned} \tag{1.2.1}$$

$\mathbb{1}\{\text{Industry} = s\}$ is an indicator variable that takes the value of 1 if $Share_{ist}$ is the portfolio share of industry s. $\boldsymbol{X}_{it}$ is a set of control variables that include

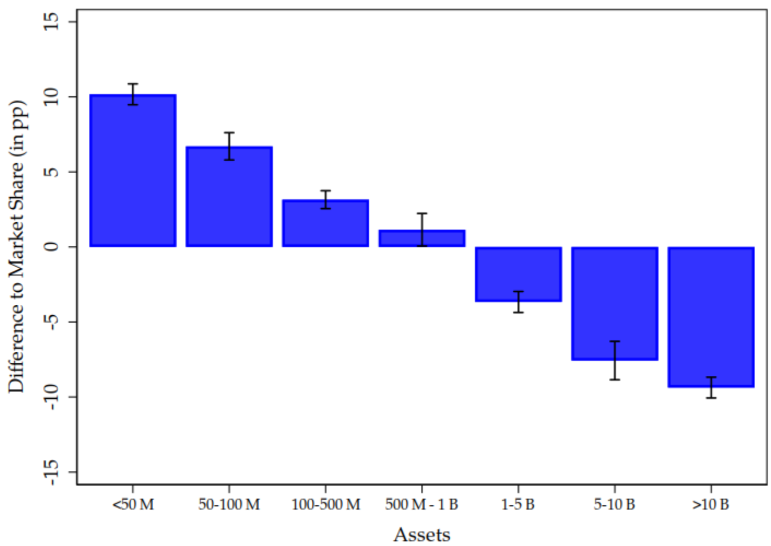
5. To form a corporate bond market portfolio, I proxy for the outstanding amount of corporate bonds in an industry sector with the offering amount obtained from Mergent FISD and track the portfolio of active bonds. I only consider bonds that appear at least once in the cleaned TRACE Enhanced. Following the standard procedure in the literature, I clean TRACE Enhanced according to the procedure laid out in Dick-Nielsen (2009) and Dick-Nielsen (2014).

insurers' financials, leverage, ROE, RBC ratio -, insurers' portfolio concentration, and industries' average credit rating. u_{is} and v_t are insurer-industry and time fixed effects. I cluster standard errors at the insurer level. The clustering accounts for the strong correlation of insurers' financials and investment behavior over time.

Figure 1.2.3. Prevalence of industry sectors and finance bond investments across size



(a) Share of insurers investing in each industry sector



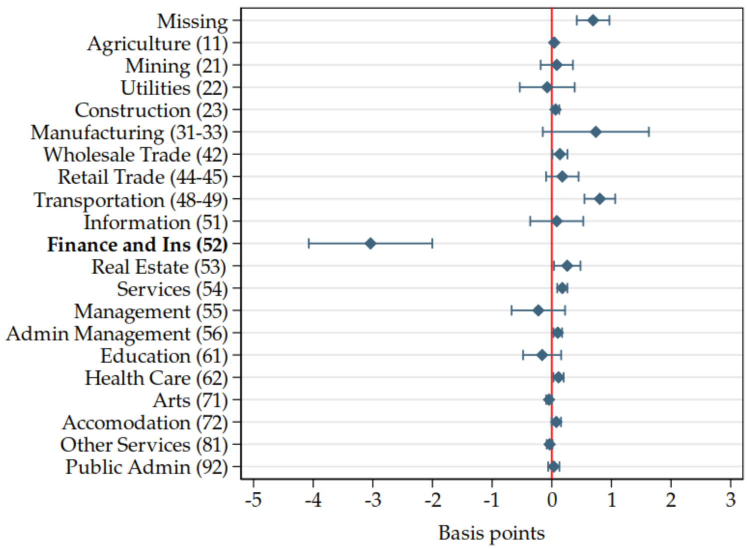
(b) Portfolio share of Finance bonds relative to market portfolio

Notes: This figure shows the (a) the share of insurers that have invested in each industry sector and the (b) average portfolio share of Finance bonds relative to the market portfolio across the seven size buckets.

Essentially, the coefficients of equation 1.2.1 give for every industry the relationship between insurers' size and insurers' portfolio share of this industry. $\beta_{Missing}$ is the relationship between size and the portfolio share for bonds of issuers that do not have an industry code; $\beta_{Missing} + \beta_s$ is the corresponding relationship for industry sector s. Figure 1.2.4 plots the coefficients and the corresponding 95%

confidence intervals. For almost all industries, the relationship between size and portfolio share is not or at most slightly significant relationship. However, there is a strong negative relationship between insurers' size and portfolio share for finance bonds. A 1 percent increase in insurers' size corresponds to a 3 basis point decrease in the portfolio share of finance bonds. To make the economic significance of this result more plastic, consider two insurers, with one double the size of the other. According to the results of Figure 1.2.4, the smaller insurer invests on average 3 percentage points less of her corporate bond portfolio in finance bonds and more in other industries.

Figure 1.2.4. Size of insurers and industry portfolio shares



Notes: This figure shows the coefficients on the industry interactions and the main term of equation 1.2.1. The caps represent the corresponding 95% confidence intervals. I control for several financial variables of the insurer, i.e., *Leverage*, *ROE* and *RBC ratio*, portfolio characteristics, i.e., the *Portfolio HHI*, and the average rating of the industry sector, *Rating*. Moreover, I include insurer-industry and time fixed effects. Standard errors are clustered at the insurer level.

In Table 1.2.2, I show that this relationship is robust to various combinations of fixed effects. Moreover, the economic magnitude lies roughly around 3 basis points per percent of assets in all specifications. This relationship does not just pertain to the corporate bond portfolio but is relevant for the entire balance sheet. In Table 1.E.2, I measure the dependent variable $Share_{ist}$ in regression 1.2.1 in terms of insurers' total fixed income portfolios or total asset investments. The size of the effect changes because the denominator is now larger; the significance, however, remains the same because insurers in my sample allocate across all sizes a constant fraction of their total assets to corporate bond investments (see Figure 1.D.3). From these observations, I derive the second fact.

Fact 2. Small insurers invest relatively more in finance bonds than large insurers.

Table 1.2.2. Insurers' size and corporate bond portfolio allocation

	Dependent variable: $Share_{ist}$				
	(1)	(2)	(3)	(4)	(5)
$Finance_s \times Log(Assets)_{it}$	-2.894***	-2.897***	-3.731***	-2.882***	-2.757***
	[-21.58]	[-21.36]	[-6.78]	[-4.94]	[-20.61]
$Log(Assets)_{it}$	0.087***	0.076***	0.693***	0.114	
	[4.49]	[3.73]	[4.96]	[0.80]	
Other industries	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	No	No	No
Time FE	No	No	Yes	No	No
Insurer-Industry FE	No	No	Yes	Yes	No
Insurer-Time FE	No	No	No	No	Yes
Industry-Time FE	Yes	Yes	No	Yes	Yes
HQ Location-Time FE	No	No	No	No	Yes
No. of obs.	551,670	532,959	530,544	530,544	544,068
R^2	0.624	0.624	0.851	0.853	0.623
Adj. R^2	0.621	0.622	0.830	0.833	0.603

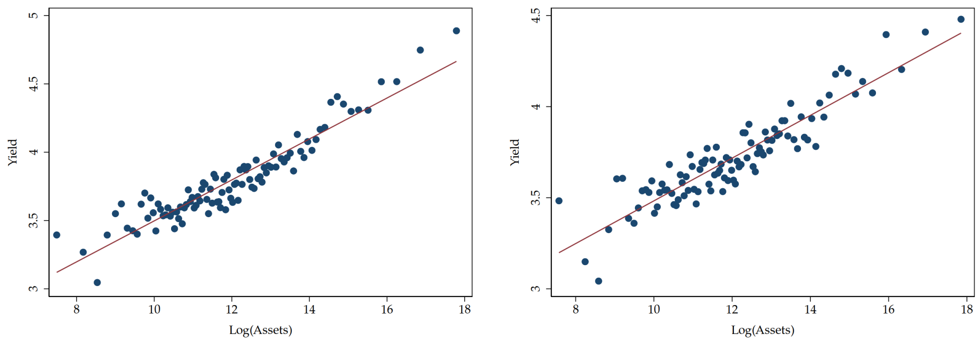
Notes: This table provides estimates for the relationship between insurance companies' size and insurers' portfolio share of Finance bonds. The dependent variable $Share_{ist}$ is the share of the corporate bond portfolio insurer i invests in corporate bonds from industry s at time t. $Log(Assets)_{it}$ is the natural logarithm of insurer i's total assets at time t. $Finance_s$ is an indicator variable that takes the value one if the dependent variable is the industry share of two-digit NAICS code 52, i.e., Finance. I control for several financial variables of the insurer, i.e., *Leverage*, *ROE* and *RBC ratio*, portfolio characteristics, i.e., the *Portfolio HHI*, and the average rating of the industry sector, *Rating*. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

The previous two facts imply that small insurers focus their investment strategy on finance bonds. Instead of having a large portfolio, they invest in a few finance bonds. Large insurers, on the other hand, invest in a broad set of securities. These differences in portfolio choice can be driven by driven by differences in yields. Becker and Ivashina (2015) show that insurers are reaching for yield in corporate bond markets by buying securities of the lowest credit quality within the risk categories defined by the NAIC. A similar mechanism could lead to small insurers predominantly investing in finance bonds. A risk argument, however, stands against this. Size is one of the most important determinants of risk (Ge and Weisbach (2021), Fama and French (1993)), hence small insurers are riskier than large insurers.[6] The larger risk on the liability side should drive them away from risky investments with higher yields. Figure 1.2.5 plots the average portfolio yield of

6. By insuring multiple individuals, insurers aim to exploit the law of large numbers which turns the individual uncertainty to certainty in the aggregate.

the corporate bond investments across size for (a) all securities and (b) only finance bonds. Small insurers report a lower average yield on their securities than large insurers. The relationship between size and portfolio yield is almost monotonically increasing, and it holds true for both all bonds and the subsample of finance bonds. Overall, large insurers invest in finance bonds with a higher yield than small insurers. This observation is consistent with the risk argument in Ge and Weisbach (2021) and other parts of the literature.

Figure 1.2.5. Portfolio yield across size



(a) All bonds **(b)** Only Finance bonds

Notes: This figure shows two binned scatter plots of the average portfolio yield of corporate bond securities across insurers' size. Panel (a) shows the average yield for all securities, panel (b) for the portfolio of Finance bonds.

To confirm this evidence that there is no reaching-for-yield mechanism driving the first two facts, I follow a procedure similar to Becker and Ivashina (2015) and Becker, Opp, and Saidi (2022). More specifically, I calculate the share of the issue acquired by insurers for each new issue.[7] I calculate this variable for each of the seven size buckets separately. As in Becker and Ivashina (2015), I proxy for the amounts acquired by insurers with the holdings reported by insurers at the end of the issuance year. Then, I run for each size bucket the regression,

$$\text{Share issue}_{b;k} \;=\; \beta \text{ Finance}_b + \gamma \text{ Yield spread}_b + \boldsymbol{\delta X} + u_t + v_{mr} + \varepsilon_b, \qquad (1.2.2)$$

where *Share issue*$_{b;k}$ is the share of the issue b held by insurers in size bucket k. *Finance*$_b$ is an indicator variable that takes the value 1 if the issue b was undertaken by a finance entity, i.e., an entity with a two-digit industry code of 52. *Yield spread*$_b$ is the yield spread of the issue, i.e., the difference between the offering yield reported in Mergent and the yield of a maturity-matched U.S. Treasury.[8]

7. Panel 1 of Table 1.E.3 provides the summary statistics of the sample.

8. As Mergent often does not report a yield spread for an issue, I calculate yield spreads from the offering yields reported by Mergent and the data on the Treasury yield curve published

$\boldsymbol{X}$ is a set of control variables, including a proxy for the liquidity of the issuance, the issuance size, several bond properties, and others. u_t and v_{mr} are time and maturity-rating fixed effects. I define six different maturity buckets for the fixed effects. Bonds with maturity less than 1 year, between 1 and 3 years, between 3 and 5 years, between 5 and 10 years, between 10 and 20 years, and greater than 20 years. I cluster standard errors at the issuer level.

With equation 1.2.2, I examine whether insurance companies of different sizes invest differently in finance and non-finance bonds. From the results above, I expect β to be significantly greater than zero for small insurers, close to zero for middle-sized insurers, and significantly negative for large ones. By controlling for various issue-level characteristics such as the yield spread, liquidity, and maturity-rating fixed effects, I control for differences in companies' investment strategies in terms of risk, liquidity, maturity, and others. In robustness checks, I add firm-level controls or match finance bonds to non-finance bonds based on a mixed matching procedure. The results are presented in Tables 1.E.4, 1.E.5, and 1.E.6 in the Online Appendix. They confirm the empirical patterns shown above. Small insurers invest more in finance issues, while large insurers invest significantly less in finance issues. These results are robust to additional firm-level controls and matching. To put a perspective on how much small insurers invest more in finance bonds, Figure 1.D.4 plots the estimates for the βs of equation 1.2.2 scaled by the mean of the dependent variable for the seven different size buckets. Comparing a finance bond with an equivalent non-finance bond, small insurers buy on average 30 percent more of the finance bond than the non-finance bond. The following third fact summarizes the previous findings.

Fact 3. Reaching for yield and other factors do not explain the size-investment relationship.

As established arguments do not explain the first two facts, finance bonds must have another property that explains the observed patterns. The issuers of finance bonds are mainly active as financial intermediaries. One of the main functions of financial intermediation is the diversification of risk. If financial institutions act on this role, their securities should have the lowest idiosyncratic risk. To proxy for the idiosyncratic risk of bonds, I calculate the variance of the error term in a standard three-factor model of Fama and French (1993). More specifically, I regress bonds' excess returns over the entire lifetime of a bond on the market spread, default spread, and term spread, i.e.,

$$\begin{aligned} R_{bt} - R_{ft} \;=\; & \beta_{b0} + \beta_{Market} \text{ Market spread}_t + \beta_{Default} \text{ Default spread}_t \\ & + \beta_{Term} \text{ Term spread}_t + \varepsilon_{bt}. \end{aligned} \tag{1.2.3}$$

by the U.S. Department of the Treasury. I interpolate between Treasury yields when the maturity of the Treasury does not match the bond's maturity.

R_{bt} is the monthly return of bond b from month $t-1$ to t. R_{ft} is the risk-free rate of return at time t proxied by the one-month Treasury bill rate. *Market spread*$_t$ is the market premium measured as the market risk factor taken from Ken French's website. *Default spread*$_t$ is the spread between BAA- and AAA-rated monthly corporate bond yields.[9] *Term spread*$_t$ is the monthly return on the Ibbotson U.S. long-term government bond index minus the one-month Treasury bill rate. I construct bond returns from TRACE after applying the standard cleaning procedure by Dick-Nielsen (2009) and Dick-Nielsen (2014), which takes out erroneous trades, cancelled trades, interdealer trades, and others. Moreover, I only consider bond returns up to one year before maturity. The bond returns are defined as,

$$R_{bt} = \frac{(P_{bt} + AI_{bt}) + C_{bt} - (P_{bt} + AI_{bt-1})}{(P_{bt-1} + AI_{bt-1})}, \tag{1.2.4}$$

where P_{it} is the last transaction price of bond b in month t; AI_t is the accrued interest of bond b in month t; C_{bt} is the coupon payment on bond b in month t. From regression 1.2.3, I estimate the error terms ε_{bt} and use the time series variance, $\sigma(\hat{\varepsilon})_b$, as the proxy for idiosyncratic risk.[10]

Panel (a) of Figure 1.2.6 shows that finance bonds have one of the lowest median $\sigma(\hat{\varepsilon})_b$ among industries. Finance bonds have the second-lowest median $\sigma(\hat{\varepsilon})_b$ for large bond issues. Only bonds from the sector "Public Administration" have lower idiosyncratic risk. As "Public Administration" consists of state-funded operations, these bonds offer even lower idiosyncratic risk. Moreover, the total issuance amount of private corporations in the sector "Public Administration" over the sample period is meager, with less than \$500 billion (see panel (b) of Figure 1.2.6).

I compare the idiosyncratic risk of finance and non-finance bonds in a matching procedure to support this first suggestive evidence. More specifically, I match finance bonds with non-finance bonds in an exact matching procedure paired with a propensity score matching. I perform an exact matching on rating, maturity buckets, issuance year, issuance size quintiles, and liquidity quintiles. After the exact matching, I apply a propensity score matching method with issuance amount and liquidity as matching variables. I proxy for liquidity with the average monthly Bid-Ask spread during the year of issuance in order to account for the fact that bonds are bought early by insurers and then held to maturity. Then, I estimate the following regression specification,

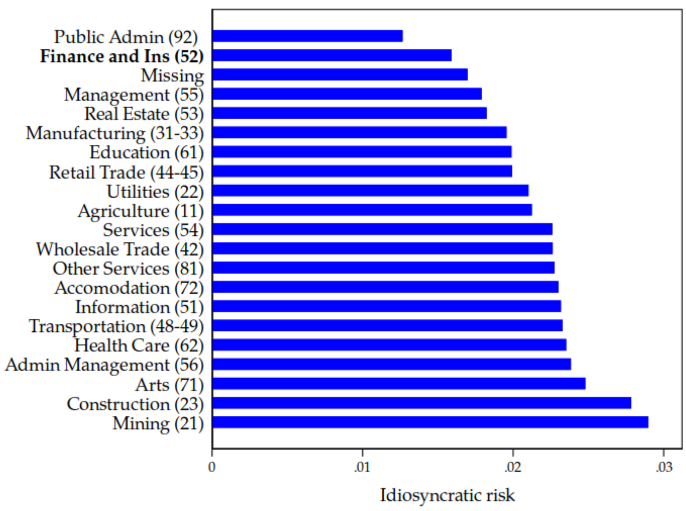
$$\sigma(\hat{\varepsilon})_b = \beta \text{ Finance}_b + \boldsymbol{\gamma X}_b + u_{ymr} + v_{gy} + \varepsilon_b. \tag{1.2.5}$$

9. The data on BAA- and AAA-rate monthly corporate bond yields, and the data on the Ibbotson U.S. long-term government bond index is taken from Welch and Goyal (2008) which is generously made available by Amit Goyal on his webpage (see sites.google.com).

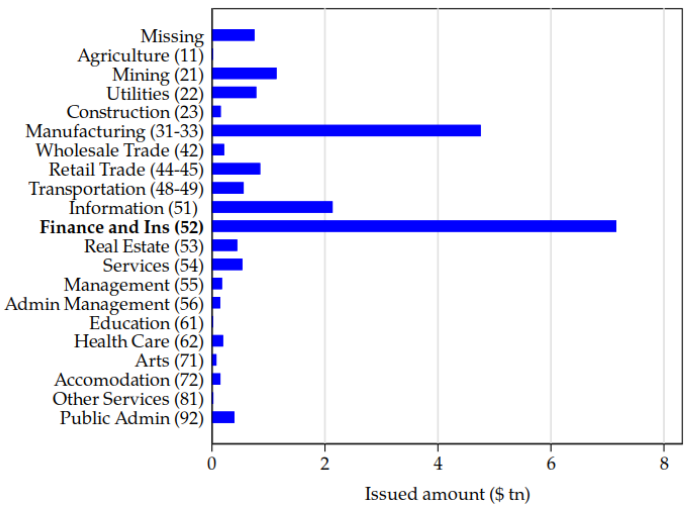
10. Panel 2 of Table 1.E.3 provides the summary statistics of idiosyncratic risk variables.

$Finance_b$ is an indicator variable that takes the value of 1 if bond b is a finance bond. $\boldsymbol{X}_b$ is a vector of controls, i.e., the $Liquidity\ at\ issuance_b$ measured as the average monthly Bid-Ask spread in the year of issuance and the $Log(Issuance\ amount)_b$. u_{ymr} and v_{gy} are issuance year-maturity bucket-rating and SIFI-year fixed effects. The dependent variable $\sigma(\hat{\varepsilon})_b$ is the estimated variance of the idiosyncratic error term in the returns multiplied by 100.

Figure 1.2.6. Idiosyncratic volatility and bond issuance



(a) Idiosyncratic volatility by industry



(b) Bond issuance by industry

Notes: This figure plots in panel (a) the median idiosyncratic volatility of large bond issues - with an issuance amount above $100 million - by industry sector and in panel (b) the total issuance over the sample period from 2010 to 2019 by industry sector.

One potential concern regarding equation 1.2.5 is that bailout expectations lead to lower idiosyncratic risk of finance bonds. As the failure of a financial institution can trigger a chain reaction and lead to severe economic losses, governments tend to rescue financial institutions' bankruptcy in case of default. If investors price this in, the lower idiosyncratic risk results from bailout expectations and not intermediary diversification. Since 2011, the Financial Stability Board ("FSB") has maintained a list of global systemically important financial institutions ("SIFIs") whose failure poses a threat to the financial system.[11] Because of their relevance for financial stability, SIFIs enjoy an implicit bailout guarantee from the government.[12] Hence, I construct an indicator variable that takes the value of 1 if the bond's issuer was listed at least once as a global systemically important financial institution in the sample period and include this variable interacted with the bond's issue year as fixed effects, i.e., v_{gy}.

Table 1.2.3 shows the results of regression equation 1.2.5. The results confirm the sector-level evidence. Finance bonds have a significantly lower idiosyncratic risk than non-finance bonds, even when controlling for bailout expectations and liquidity, maturity, and rating differences. Consistent with the idea that diversification needs a certain size, the result is stronger for larger bond issues. I compute quintiles of the cross-sectional distribution of bonds' *Issuance Amount* and separately estimate equation 1.2.5 for each of the five size quintiles. Finance bonds have more idiosyncratic risk than non-finance bonds among the smallest issues, but from the third quintile on, the difference is negative and significant. Tables 1.E.7 and 1.E.8 show the results of two robustness checks. In Table 1.E.7, I estimate the residuals from a five-factor model that adds to the three-factor model from Fama and French (1993) the liquidity factor developed by Dick-Nielsen, Feldhütter, and Lando (2012), and the TED spread, that is, the difference between the 3-month London Interbank Offered Rate (LIBOR) and the 3-month Treasury bill rate. In Table 1.E.8, I apply a less restrictive matching procedure in the first step and match only on size and liquidity quintiles as well as year of issuance. The results stay qualitatively the same. Therefore, I can state the last fact.

Fact 4. Finance bonds have lower idiosyncratic risk than bonds of other industries.

The first three facts presented in this section create a paradox. On the one hand, small insurers are riskier than large insurers. On the other hand, they do

11. Global systemically important financial institutions are large banks and insurance companies that pose "greater risks [...] to the global financial system" (fsb.org). For a complete list, see fsb.org.

12. Ueda and Weder di Mauro (2013) and Warburton, Anginer, and Acharya (2022) show that SIFIs' funding costs and credit spreads still reflect investors' expectations of an implicit government guarantee. However, Berndt, Duffie, and Zhu (2023) document for banks a decline in the probability of a government bailout after the global financial crisis and, in turn, a decrease in the value of the implicit guarantee.

not invest in a broad set of corporate bond securities but predominantly invest in bonds issued by other financial companies. Reaching-for-yield or other investment goals cannot explain these observations. The last fact then presents a new property of bonds issued by financial institutions. In the next section, I provide causal evidence that explains insurers' investment behavior as a result of their efforts to minimize their exposure to idiosyncratic risks.

Table 1.2.3. Idiosyncratic risk of finance versus other bonds

	Dependent variable: $\sigma(\hat{\varepsilon})_b$						
			Quintiles of *Issuance amount*$_b$				
			1st	2nd	3rd	4th	5th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Finance$_b$	-0.115***	-0.128***	0.836***	0.912***	-0.231*	-0.131*	-0.247***
	[-3.18]	[-3.34]	[4.68]	[4.67]	[-1.89]	[-1.91]	[-5.86]
Liquidity at issuance$_b$	0.274***	0.275***	0.225***	0.146	0.237***	0.723***	0.314***
	[7.93]	[7.84]	[3.03]	[1.55]	[2.93]	[5.56]	[2.78]
Log(Issuance amount)$_b$	0.076***	0.067***	0.481***	0.361*	-0.201	0.079	0.235***
	[3.90]	[3.38]	[2.70]	[1.65]	[-1.53]	[0.34]	[4.05]
Issue Year-Maturity-Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issue Year-SIFI FE	No	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	6,032	6,026	277	289	1,305	1,464	2,678
R^2	0.365	0.369	0.453	0.605	0.308	0.475	0.485
Adj. R^2	0.331	0.333	0.386	0.552	0.173	0.397	0.437

Notes: This table shows estimates for regression equation 1.2.5. The sample comes from a mixed matching procedure. In the first step, Finance bonds are matched to non-Finance bonds with exact matching on the following characteristics: credit rating at issuance, maturity bucket, quintile of the cross-sectional distribution of issuance size, quintile of the cross-sectional distribution of liquidity, and year of issuance. Within an exact matching, I apply a propensity score matching method based on the *Liquidity at issuance* and *Log(Issuance amount)*. The dependent variable $\sigma(\hat{\varepsilon})_b$ is the variance of residuals estimated from Fama-French three-factor models. *Finance*$_b$ is an indicator variable that takes the value one if a financial institution has issued the bond *b*. *Liquidity at issuance*$_b$ is the average Bid-Ask spread in the year of issuance of bond *b*. *Log(Issuance amount)*$_b$ is the natural logarithm of the amount issued of bond *b*. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

1.3 The 2017 Bond ETF Reform

In this section, I exploit a regulatory reform in 2017 to show that diversification motives drive insurers' finance bond investments. The reform extended insurers' access to bond ETFs. Hence, the reform broadened insurers' opportunities to invest in a low-cost, diversified portfolio of corporate bonds. Consistent with the view of finance bonds' implicit diversification function, finance bonds became less attractive for small insurers after the reform.

During the Spring National Meeting in April 2017, the NAIC adopted changes to Statutory Issue Paper No. 26 which set the scope of the definition of a fixed income security for insurers. More specifically, the Statutory Accounting Principles Working Group (SAPWG) implemented a new valuation approach for bond ETFs that substantially reduced capital requirements for investments in these instruments. This regulatory change made it viable for insurers to use ETFs as equivalents to bonds like U.S. Treasuries or corporate bonds.

Before 2017, the NAIC defined any investments in ETFs as common stocks because insurers acquired shares of a fund rather than a fixed income security like a U.S. Treasury. Hence, the NAIC had insurers account all ETFs like common stocks at fair value. In 2013, however, the SAPWG acknowledged in their December meeting that there were various issues with this treatment of ETFs. This induced the SAPWG to start efforts to "clarify and improve the statutory accounting guidance" (National Association of Insurance Commissioners (2013), p. 10-134) concerning ETFs (and other investments that did not fit the NAIC's standard definition of a bond at this time). During the process, the SAPWG collected the opinions of various state regulators, industry representatives, and investment advisors such as BlackRock. The project resulted in two important changes regarding bond ETFs. First, the new version of Statutory Issue Paper No. 26 included a clear definition of bond ETFs and laid out consistent reporting guidelines that facilitated the identification of ETF investments in insurers' financial statements. Second, the NAIC adopted the "systematic value" approach proposed by BlackRock to determine the book value of bond ETFs. The systematic value approach is considered a "look-through" accounting approach, which resembles the amortized cost approach for normal bonds. Under this approach, the book value of an ETF is determined based on the cash flows generated from the basket of underlying bonds. Hence, the systematic value of an ETF is substantially less volatile than the fair value.[13] From December 31, 2017, insurers could choose whether they account bond ETFs at fair value or, after recognition by the NAIC's Securities Valuation Office, at systematic value. However, not all states adopted the reform. For example, the state of New York allowed NY-domiciled insurers only in December 2021 to account bond ETFs at systematic value.[14]

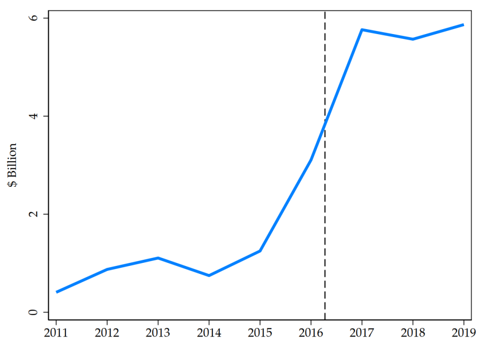
The reform leveled regulatory treatment between bonds and bond ETFs and gave insurers access to a diversified investment tool at no additional (regulatory) cost. Thereby, this ETF reform substantially relaxed the liquidity cost constraints insurers faced on OTC bond markets. Anecdotal evidence suggests that the reform induced small insurers to reduce their corporate bond investments and instead in-

13. Figure 1.D.8 compares the value of an ETF share with the systematic value approach and the fair value approach. For details on the calculation of an ETF's systematic value, see State Street Global Advisors (2021).

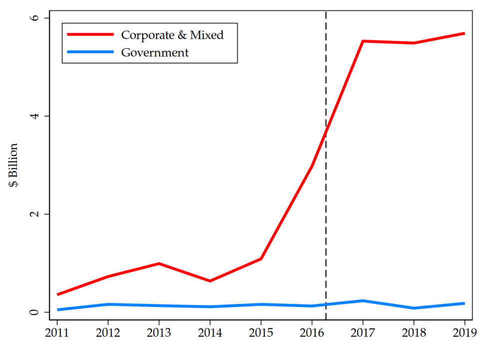
14. See ft.com.

vest in bond ETFs. Earley, Oliver, and Stack (2017) report that some insurers even replaced their entire bond portfolio with bond ETFs. Figure 1.3.1 yields first empirical evidence consistent with the anecdotal evidence. Panel (a) shows the bond ETF investments reported by insurance companies from 2011 to 2019.[15] From year-end 2016 to year-end 2017, insurers doubled their bond ETF investments from $3 billion to almost $6 billion. However, panel (b) shows that the increase in holdings was not equally split across all ETFs. Insurers focussed their investments on ETFs exclusively investing in corporate securities or a mix of corporate and government securities. In contrast, the investments in ETFs that were exclusively investing in government securities remained low. Note, however, that the total investments in bond ETFs remained rather low and did not exceed $6 billion at the end of 2019. The overall low level of investments is partly due to important states with many insurance companies like New York not approving the new regulation. But it also hints at the fact that, in particular, small insurers made use of the regulatory changes as was intended by the reform (see Pullara (2017)).

Figure 1.3.1. Total bond ETF investments by insurers



(a) All



(b) By ETF type

Notes: This figure plots the total year-end bond ETF investments reported by insurers in NAIC Schedule D Part 1 from 2011 to 2019 for (a) all ETFs and (b) split by ETF type. The investments are measured in actual cost reported by insurers, i.e., the acquisition price of the bond ETF. The dashed line represents April 8, 2017, the day the Statutory Accounting Principles Working Group passed the bond ETF reform. It was effective on December 31, 2017.

I exploit the NAIC regulatory reform and apply a diff-in-diff strategy to show that finance bonds served insurers as a diversification tool. If small insurers invested in finance bonds because they provided a tool to avoid the high transaction costs on corporate bond markets while still maintaining diversification, then the regulatory reform should have made finance bonds less attractive for them. Hence,

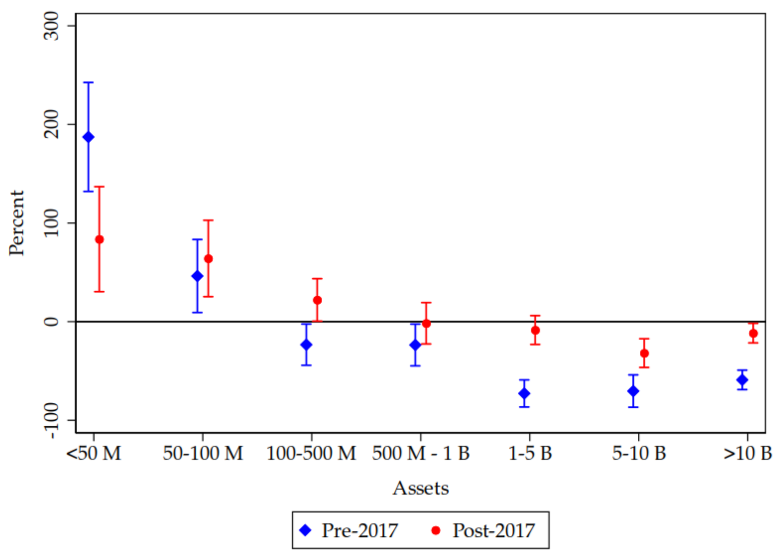
15. The data on insurers' bond ETF investments does not contain any ETF investments prior to 2011.

analogous to the empirical tests for a possible reaching for yield mechanism, I run the diff-in-diff regression,

$$\begin{aligned} \text{Share issue}_{b;k} &= \beta_{Post}\ \text{Post}_t \times \text{Finance}_b + \beta_{Pre}\ \text{Finance}_b \\ &\quad + \gamma\ \text{Treasury spread}_b + \boldsymbol{\delta X} + u_t + v_{mr} + \varepsilon_b. \end{aligned} \tag{1.3.1}$$

As above, *Share issue*$_{b;k}$ is the share of the issue b held by insurers in size bucket k. *Finance*$_b$ is an indicator variable that takes the value 1 if the issue b was issued by a finance entity, i.e., an entity with a two-digit industry code of 52. *Post*$_t$ is an indicator variable that takes the value 1 for 2017 and afterwards. *Treasury spread*$_b$ is the Treasury spread of the issue, i.e., the difference between the offering yield reported in Mergent and the yield of a maturity-matched U.S. Treasury. $\boldsymbol{X}$ is a set of control variables, including a proxy for the liquidity of the issuance, the issuance size, several bond properties, and others. u_t and v_{mr} are time and maturity-rating fixed effects. I cluster standard errors at the issuer level. In my baseline specification, I exclude issues from 2014 to 2016. The NAIC proposed the original statutory issue paper in 2014, and the discussion spanned from 2014 to 2016. Figure 1.3.1 shows that some insurers tried to anticipate the regulatory change and invested before the reform. In robustness checks, however, I also include 2014 to 2016.

Figure 1.3.2. Impact of the 2017 NAIC bond ETF reform on the use of finance bonds



Notes: This figure plots the β coefficients of regression 1.3.1 for the seven different size buckets scaled by the mean of the dependent variable. It replicates the approach from Becker, Opp, and Saidi (2022) and considers only new issues proxied for by insurers' year-end holdings in the year of issuance.

Figure 1.3.2 visualizes the results of equation 1.3.1. The blue graph shows β_{Pre} while the red graph shows $\beta_{Pre} + \beta_{Post}$. Before the reform, small insurers had invested significantly more in finance bonds than non-finance bonds, while large insurers underinvested. After the reform, however, finance bonds have become much less important for small insurers. As a robustness check, Figure 1.D.5 in the Online Appendix repeats equation 1.3.1 but includes all sample years. The results are qualitatively similar. The reform has made finance bonds less attractive for small insurers.

1.4 A Model of Intermediated Diversification

This section develops a model which rationalizes the two previous empirical findings. First, small insurers only invest in a few corporate bond securities, the majority of them issued by finance entities. In contrast, large insurers buy a broad, diversified portfolio of many securities from different industries. Second, a regulatory reform that extended insurers' access to bond ETFs made finance bonds less attractive. The model explains insurers' investment behavior as a result of a tradeoff between transaction and regulatory costs. This tradeoff is more stringent for small insurers because of the size penalty on insurance markets. Finance bonds pose a solution to small insurers' dilemma as they allow them to diversify their corporate bond portfolio while saving on transaction costs. Simulating the model, I analyze several counterfactuals to derive further predictions for the empirical analysis.

1.4.1 Model Setup

The environment. There are two time periods, $t = 0$ and $t = 1$, and two agents, a bank and an insurer. Agents do not discount future payoffs. In period 0, there is an asset market with N risky assets. Each risky asset creates a stochastic return R_i, $i = 1, \ldots, N$, in period 1. The returns follow a factor structure with K risk factors f_k, $k = 1, \ldots, K$, and an idiosyncratic component ε_i, i.e.,

$$R_i \;=\; \beta_{i0} + \sum_{k=1}^{K} \beta_{ik} f_k + \varepsilon_i. \tag{1.4.1}$$

The K risk factors are independently and normally distributed with mean μ_k and variance σ_k^2; the idiosyncratic error terms are independently and identically distributed with mean 0 and variance σ_ε. The idiosyncratic volatility σ_ε is proportional to the asset's expected return, i.e., there exists the classical risk-return relationship. Moreover, the idiosyncratic risk is independent of the risk factors. Hence, to minimize the idiosyncratic risk, an investor would have to buy all N assets. Purchasing a risky asset, however, comes with a fixed transaction fee c. The fee c has to been paid for each positive amount purchased of an asset. Eventually, the fixed cost introduces a per-unit transaction cost function $c(x) = \frac{c}{x}$ which is strictly convex in $x > 0$, i.e., $c'(x) < 0$ and $c''(x) > 0$ for $x > 0$. In case of no trade, no transaction costs accrue, $c(0) = 0$. These properties of $c(x)$ mirror evidence from transaction data in corporate bond markets (see Edwards, Harris, and Piwowar (2007)).

The bank. The bank is financed with deposits D and bonds B.[16] The deposits pay out an interest rate of r in period 1, and the bonds pay out a return of R_B. On the asset side, the bank invests these funds in the N risky assets and has to pay the per-unit transaction cost $c(x)$ for each asset bought. Let $\boldsymbol{w_B} = (w_{B1}, \ldots, w_{BN})^T$ be the portfolio weights of the bank. I do not specify an optimization problem for the bank but assume that the bank chooses some portfolio weights $\boldsymbol{w_B}$. The portfolio $\boldsymbol{w_B}$ determines how diversified the bank is. As a baseline scenario, I assume that the bank chooses $w_{Bn} = \frac{1}{N}$ for all $n \in \{1, \ldots, N\}$. In this case, the bank perfectly diversifies away the idiosyncratic risk.[17] In period 1, the bank earns returns $\sum_i w_{Bi} \tilde{R}_i$ and pays out the promised returns on its liabilities r and R_B. If the returns of the bank's portfolio do not suffice to cover the liabilities, the bank defaults, which is the case if

$$\sum_i w_{Bi} \tilde{R}_i \; < \; \frac{D}{D+B} \cdot r + \frac{B}{D+B} \cdot R_B. \tag{1.4.2}$$

In case of a bank default, the creditors seize the existing assets according to their share of liabilities. I assume that the bank is large enough such that the transaction fee is of no concern to the bank.[18]

The insurer. The insurance company is endowed with assets A_0 in period 0. With the assets A_0, the insurer forms a portfolio consisting of the risky assets R_i and the bank bonds. Let $\boldsymbol{w_I} = (w_{I1}, \ldots, w_{IN}, w_{IB})^T$ denote the portfolio of the insurance company. On the liability side, the insurer has underwriting liabilities L_0 and equity $A_0 - L_0$ in period 0. These underwriting liabilities evolve in period 1 with some factor $\tilde{\mu}_L$. Analogous to the assets, the liability factor $\tilde{\mu}_L$ follows a factor structure with loadings $(\beta_{L0}, \beta_{L1}, \ldots, \beta_{LK})$, and an idiosyncratic error term ε_L, i.e.,

16. In the model, I term the financial institution as a bank. The assumptions, however, could imply any (large) financial institution that takes intermediary function in the economy, e.g. hedge funds or insurance companies.

17. This assumption mirrors the approach of Dick-Nielsen, Feldhütter, and Lando (2023) who assume that financial institutions have little idiosyncratic risk because they hold a diversified portfolio of corporate bonds (loans).

18. Interpreting the fixed transaction fee as convex per-unit cost, this assumption means that if the bank marginally adjusts one position, the size of the transaction is still large enough that there is no substantial change in the per-unit transaction costs. Hence, the bank is not constrained in her portfolio choice.

$$\mu_L = \beta_{L0} + \sum_{k=1}^{K} \beta_{Lk} f_k + \varepsilon_L. \tag{1.4.3}$$

The idiosyncratic error term ε_L has mean zero and variance σ_L; it is independent of all risk factors and all idiosyncratic error terms ε_i of the assets. The factor structure formulation captures the properties of both life and P&C insurers' underwriting liabilities. life insurers' liabilities depend more on the evolution of the risk factors, i.e., their liability loadings significantly differ from zero. For example, with products like variable annuities, which encompass minimum return guarantees, life insurers essentially insure policyholders against market risk. Hence, their underwriting liabilities comove with the market risk factor.[19] On the other hand, for P&C insurers, the idiosyncratic error term is the important driver of their underwriting liabilities, while their liability loadings are close to zero because P&C insurers mainly sell protection against damages from events that are unrelated to market factors, such as natural disasters, theft, and others.

The insurer is subject to risk-based capital (RBC) regulation. More specifically, the insurer has to pay regulatory cost $K(\frac{A}{L})$ in period 1, which is a function of its asset-liability ratio. The regulatory cost mirrors the NAIC's RBC regulation which prescribes that insurers hold enough capital to cover their liabilities. If an insurer's RBC ratio breaches pre-defined thresholds, the regulator will prescribe or take action to ensure the future solvency of the insurer. In the most extreme case, the regulator takes over the insurance company and initiates a resolution mechanism. In the model, I assume that the regulatory cost is continuous and strictly convex in the asset-liability ratio, i.e., $K'(\cdot) < 0$, and $K''(\cdot) > 0$.

The optimization problem. The insurance company chooses its portfolio $\boldsymbol{w}_I$ to maximize its expected wealth. The maximization problem is given by,

$$\begin{aligned} \max_{w_I} \quad & E\Big[A_0\Big(\underbrace{\sum_{i=1}^{N} w_{Ii}\tilde{R}_i - \mathbb{1}\{w_{Ii} > 0\}\frac{c}{A_0}}_{=\text{net return risky assets}} \\ & + \underbrace{w_{IB}\tilde{R}_B - \mathbb{1}\{w_{IB} > 0\}\frac{c}{A_0}}_{=\text{net return bank bonds}}\Big) - \tilde{L}_1 - \underbrace{K\Big(\frac{\tilde{A}_1}{\tilde{L}_1}\Big)}_{=\text{reg. cost}}\Big]. \end{aligned} \tag{1.4.4}$$

The insurer's expected wealth in period 1 consists of three parts. The first part are the expected net returns on the insurer's assets. The returns are stemming from both the portfolio of risky assets and the bank bonds. The second part is the

19. Figure 1.D.6 shows the correlation of changes in insurers' annual total liabilities with the market risk factor. The correlation coefficients are positive for life insurers and larger than the corresponding coefficients for P&C insurers. Moreover, the coefficients are larger in magnitude for life insurers which is consistent with larger life insurers' focus on variable annuity products.

expected value of the insurer's underwriting liabilities in period 1. Finally, the last part is the expected regulatory cost. To maximize expected wealth in period 1, the insurer has three conflicting goals. First, the insurer aims to increase the expected net return on the asset portfolio. To achieve higher expected returns, the insurer needs to take on more risk. Second, the insurer aims to minimize the transaction costs of building the asset portfolio. The transaction costs are minimal, if the insurer invests all funds in a single asset. Third, the insurer aims to minimize the regulatory cost. For this, the insurer must both maintain a constant asset-liability ratio and avoid unnecessary variation on the asset side. The former prescribes that the portfolio recreates as closely as possible the factor structure of the liability side; the latter that the portfolio contains all N assets as this minimizes the impact of the idiosyncratic error term of the assets.

The challenge for the insurer is to balance the goal of minimizing regulatory costs with the goals of minimizing transaction costs and maximizing expected returns. A narrow portfolio of few securities will be cheaper than a broader portfolio of the same size because the insurer has to pay fewer times the transaction fee c.[20] However, a narrow portfolio comes at the cost of higher idiosyncratic risk. The severity of this trade-off depends on the size of the insurer. Small insurers face greater difficulties as the transaction fee disproportianately increases their total transaction costs in the number of trades. On the other hand, large insurers naturally trade in large quantities and, thereby, do not face a transaction cost constraint.

1.4.2 Computational Solution

Parameter choices. Because there is no analytical solution for the maximization problem 1.4.4, I simulate the model. I use a combination of data sources and assumptions to set the parameters of the model. As a risk factor, I use the market risk factor, i.e., $K = 1$. I calculate the empirical distributions over 40 states which partition the historical state set of the market risk factor. As in the previous section, I take the market spread data from Ken French's website. I set the number of assets to $N = 4$. The asset loadings are randomly drawn from a sample of estimated factor loadings. To estimate factor loadings, I take the bond returns constructed from TRACE transaction data (see above). Then, I estimate for each bond separately, the β-coefficient for a simple risk factor model with market risk as the only factor. With a random draw I get the loadings of the four representative assets. Analogously, I estimate the factor loadings of insurers' liabilities in regressions of changes in insurers' annual liabilities on the market risk factor. As with the risky assets, I randomly draw from the sample of insurers' loadings. The idiosyncratic variance of each asset is proportional to the expected returns by the factor 2.

20. In the transaction cost interpretation, the convexity of $c(x)$ penalizes small lot sizes.

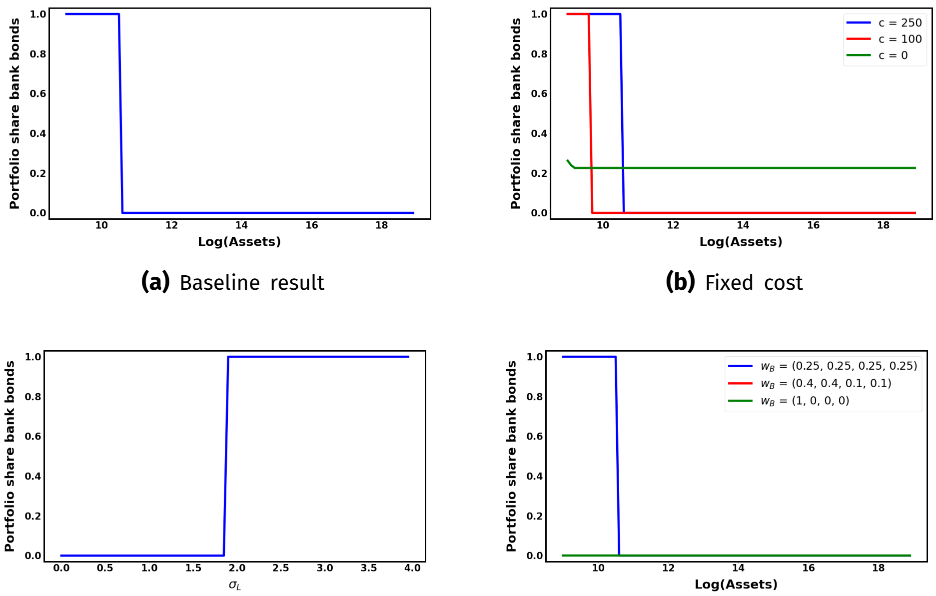
The idiosyncratic liability variance is initially fixed at 2.2 which corresponds to the maximum of estimated idiosyncratic liability variances; the asset-liability ratio in period 0 is set to 0.6. For the transaction fee c, I initially assume a value of \$250,000. Instead of a continuous regulatory cost function, I use in the simulation a discontinous regulatory cost function $K(\frac{A}{L})$ to mirror more closely actual RBC regulation. For the bank, I assume a deposit rate r of 0% - close to the national deposit rate of U.S. banks between 2010 and 2019 -, and a promised return on bonds R_B of 7% - the average coupon of finance bonds issued between 2010 and 2019. The bank's portfolio weights are initially such that the bank achieves maximum diversification with regard to the idiosyncratic risk, i.e., the bank equally splits its funds across all bonds. I set the size of the bank sufficiently large such that transaction fees are no constraint for the bank.

Results. To examine how the insurer's portfolio choice depends on her size, I solve the model for a grid of values of A_0 and plot the results of w_B^* over the set of values for A_0. First, I solve the baseline version of the model with the parameter choices described above. Panel (a) of Figure 1.4.1 shows the results of this baseline scenario. The results fit the motivating observations. If the insurer is small, i.e., A_0 is sufficiently small, she exclusively invests in the bank bonds. When the insurer is too small, the transaction fee c makes the acquisitions of each of the four risky assets disproportianately more expensive than acquiring the bank bond. Despite the lower returns of the bank bonds, the insurer invests all assets in the bank because the gain in expected returns from choosing any portfolio of risky assets instead of the bank bonds is smaller than the additional transaction and regulatory costs.

However, after a threshold $\underline{A}$, the insurer chooses to not invest anymore in the bank bonds and dedicates her entire portfolio to the risky assets. In this case, the insurer is large enough such that the return differential between a diversified portfolio of risky assets and bank bonds outweighs the additional transaction cost caused when acquiring smaller lot sizes of the four individual assets. Hence, the model explains small insurers' decision to keep narrow corporate bond portfolios and the negative relationship between insurers' size and the portfolio share insurers allocate to bank bonds.

After this baseline result, I now vary several parameters of the model to derive predictions that I can test with the data. First, I examine the effect of the 2017 bond ETF reform in the model. The 2017 bond ETF reform essentially posed a change in the fixed transaction fee c. Hence, I solve the model under two alternative scenarios for c. In the first scenario, I assume that c is substantially lower than in the baseline case, i.e., at \$100,000. In the second scenario, I assume no transaction costs, i.e., $c = 0$.

Figure 1.4.1. Model simulation



(a) Baseline result

(b) Fixed cost

(c) Liability risk

(d) Bank diversification

Notes: This figure plots the results of the model simulation. Panel (a) shows the results of the baseline scenario, panel (b) of the baseline scenario and two alternative scenarios with lower fixed cost c, panel (c) of a scenario with fixed insurer size A_0 across a grid of values of the idiosyncratic liability risk σ_L, and panel (d) of the baseline scenario and two alternative scenarios with less diversified bank portfolios w_B.

Panel (b) of Figure 1.4.1 plots the results for the three different scenarios. In the case of a smaller transaction fee, the threshold $\underline{A}$ is shifted to the left relative to the baseline scenario. Because the size penalty for corporate bond portfolios has become smaller, insurers will quicker move away from a “bank bond portfolio”. Hence, a decrease in the transaction fee implies that the size-investment relationship is weaker than in the baseline scenario. In the case of no transaction costs, the bank’s diversification function becomes irrelevant to the insurer as she can build a perfectly diversified portfolio at no cost. The insurer still uses the bank bonds to complement her portfolio for lower idiosyncratic risk. However, the share of bank bonds in the portfolio is also for small insurers closer to 0 than to 1 and does not change across size. The size-investment relationship breaks down in the case of no transaction costs. I summarize these results in the following prediction.

Prediction 1. A change in the transaction costs on corporate bond markets, alternates insurers’ use of finance bonds.

Second, I analyze the effect of the idiosyncratic volatility of insurers’ liabilities, i.e., heterogeneity in σ_L. I fix the insurer’s asset size to \$35 million as this insurer would invest her entire portfolio in bank bonds under the baseline scenario. Then, I solve the model for a grid of values of σ_L which ranges from no idiosyncratic liability risk, i.e., $\sigma_L = 0$ to high idiosyncratic liability risk, i.e., $\sigma_L = 4$ - the baseline idiosyncratic liability risk was at $\sigma_L = 2.2$.

Panel (c) of Figure 1.4.1 shows the results. With larger idiosyncratic volatility, the insurer invests more in the bank bonds. The idiosyncratic volatility of insurers' liabilities drives the insurer's risk-taking on the asset side through the regulatory cost. For a given portfolio w_I, an increase in σ_L increases the probability mass at the tails of the distribution of $\frac{A_1}{L_1}$. As the regulatory cost is higher for more fat-tailed distributions, the insurer will have to counteract by decreasing the risk on the asset side. Hence, as the bank bond offers a diversification service, the insurer invests more in the bank bonds. I summarize this result in the following prediction.

Prediction 2. Insurers with more idiosyncratic liability risk invest more in finance bonds.

Lastly, I examine the effect of the bank's asset portfolio on insurer's choice to invest in bank bonds. The insurer's main motivation to invest in the bank bonds instead of directly acquiring the risky assets roots in the bank's diversification function. The bank offers via the bank bonds a diversification service to the insurer which small insurers value because of the regulatory and transaction cost constraints. In the baseline scenario, I assume a perfectly diversified bank which equally splits the funds $D + B$ across all assets. Now, I consider two alternative scenarios where the bank deviates from this diversified portfolio. In the first scenario, the bank equally allocates 40 percent of the funds to each of the first two risky assets and only 10 percent to each of the other two risky assets. In the second scenario, the bank invests only in one of the risky assets.

Panel (d) of Figure 1.4.1 shows the size-investment relationship for the baseline scenario and the two more concentrated bank portfolios. With the concentrated bank portfolios, the insurer never invests in the bank bonds and the negative-size investment relationship breaks down. As the portfolio of the bank becomes less diversified, the bank bonds carry more of the idiosyncratic risk which insurers want to avoid. Hence, the cost advantage of bank bonds decreases in the concentration of the bank's portfolio. With the cost advantage decreasing, also the insurer switches from bank bonds to a portfolio of risky assets. In the two scenarios, the insurer does not invest in the bank bonds no matter the insurer's size. In the case of the bank portfolio concentrated on the first risky asset, the bank bonds are useless because they cap the risky asset's returns in the good states while the insurer still has to carry the cost of the bad states. In the case of the portfolio tilted towards the first two risky assets, the bank overweights assets with low returns. Hence, the bank bonds become less attractive to the insurer.

Taking this result to the real world with many different financial institutions whose portfolios vary in the degree of diversification, it follows that small insurers have a taste for finance bonds of diversified financial institutions while large insurers will invest in less diversified, specialized financial institutions. Put differently, the model predicts that small insurers mainly hold bonds of financial institutions which are diversified across many different industries and asset classes while large insurers hold bonds of specialized financial institutions which perform fewer intermediation services. I summarize this result in the following prediction.

Prediction 3. Small insurers' invest more in finance bonds issued by diversified financial institutions while large insurers' invest more in finance bonds issued by specialized financial institutions.

1.5 Empirics

In this section, I present empirical evidence that confirms the second prediction derived from the model. I exploit several heterogeneities in insurers' liability side that determine insurers' risk-taking ability on the asset side. More specifically, I use variation in the spatial and business concentration of insurers' underwriting business and their access to external and internal capital due to their organizational features. Consistent with the model's prediction, lower risk on the liability side correlates with lower investments in finance bonds.

1.5.1 Geographic Concentration and Product Focus

Insurers' main source of funding is their underwriting business. More specifically, insurers have to account for a reserve on their liability side which should cover both losses that already occurred but are not yet paid and future losses (and related costs). Hence, these variables' (expected) volatility determines insurers' need to diversify their asset side.[21] Besides the economies of scale in the underwriting business, insurers can manage the risk of their liability side by insuring uncorrelated risks. One option is to underwrite contracts in multiple lines of business, e.g., homeowners insurance, auto coverage, liability coverage, and others. If the perils are uncorrelated, then an insurer that offers multiple products faces lower volatility than a focused insurer of the same size. The model predicts the latter insurer should invest a larger portfolio share in finance bonds. Another option is to spread the underwriting business across multiple geographic areas. For example, consider two insurers of the same size, one concentrating its business in Florida and the other underwriting policies in Florida, Kentucky, and Wyoming. When a natural disaster now hits Florida, both insurers face exposure, but the former more than the latter because a larger share of the former's insurance policies trigger payouts. Hence, the Florida-focused insurer will have a more volatile liability

21. This argument works analogously to Mansi and Reeb (2002) and Hann, Ogneva, and Ozbas (2013) that show that business diversification reduces firms' riskiness.

side. According to the model's predictions, this insurer will invest more in finance bonds.

To test these predictions, I create six proxy variables that capture the mechanisms derived above, three proxies for the geographic properties and three for the product structure. From Schedule T of the NAIC statutory filings, I get detailed information on the premiums written by insurers in U.S. states and territories for each year. From this data, I construct three variables. *Spatial HHI*$_{it}$ is the Herfindahl-Hirschman index (times 100) of premiums written by insurer i in year t across the 50 U.S. states and the District of Columbia; *Active states*$_{it}$ is the share (in percent) of the 51 local markets where insurer i has written positive premiums in year t. As a third proxy, I calculate the *Spatial concentration ratio*$_{it}$ of insurers' premiums. *Spatial concentration ratio*$_{it}$ is the share (in percent) of total premiums written that insurer i has collected in year t from the state with the largest amount of premiums written.

Table 1.5.1. Summary statistics for risk constraints

Panel 1: Geographic diversification								
	N	Mean	SD	1st	25th	Median	75th	99th
Spatial HHI	21,096	48.29	39.28	3.88	9.40	35.29	99.94	100.00
Active states	21,096	43.78	41.84	1.96	3.92	23.53	96.08	100.00
Spatial concentration ratio	21,096	56.68	35.45	8.29	20.82	52.18	99.97	100.00
Panel 2: Business diversification (only P&C)								
	N	Mean	SD	1st	25th	Median	75th	99th
Business HHI	17,645	66.88	29.39	17.00	39.51	67.01	100.00	100.00
Active lines	17,645	34.39	23.97	7.69	7.69	30.77	53.85	84.62
Business concentration ratio	17,645	61.76	34.40	6.27	27.66	63.92	100.00	100.00

Notes: This table shows the summary statistics for the underwriting risk factors. In Panel 1, *Spatial HHI* is the Herfindahl-Hirschman index (times 100) of premiums written by insurer i in year t across the 50 US states and the District of Columbia; *Active states* is the share (in percent) of the 50 US states and the District of Columbia where insurer i has written positive premiums in year t; and *Spatial concentration ratio* is the share (in percent) of total premiums written that insurer i has written in year t in the state with the largest amount of premiums written. In Panel 2, *Business HHI* is the Herfindahl-Hirschman index (times 100) of premiums written by insurer i in year t across 13 insurance lines; *Active lines* is the share (in percent) of the 13 insurance lines where insurer i has written positive premiums in year t; *Business concentration ratio* is the share (in percent) of premiums written by insurer i in year t in the product category with the largest amount of premiums written.

I follow a similar strategy for the three proxy variables that capture the underwriting business's product structure. P&C insurers must report the share of premiums underwritten in each line, such as auto insurance, homeowners insurance, workers' compensation, and others. Analogous to the three proxies for the geographic structure, I build *Business HHI*$_{it}$, the Herfindahl-Hirschman index (times 100) of premiums written by insurer i in year t across the 13 insurance lines I see in the data; *Active lines*$_{it}$, the share (in percent) of the 13 insurance lines where insurer i has written positive premiums in year t; and *Business concentration ratio*$_{it}$, the share (in percent) of premiums written by insurer i in year t in the product category with the largest amount of premiums written.[22] Table 1.5.1 shows summary statistics for all underwriting risk proxies. Panel 1 shows that a significant part of the insurers is only operating in a single state - the 75th percentile of *Spatial HHI* is close to 100 -, and Panel 2 shows that many P&C insurers focus on one product - the 75th percentile of *Business HHI* is 100. This fact is partly explained by the regulatory landscape for insurance companies in the U.S., where insurance regulation is subject to state law. Instead of having one company, some insurance groups conduct operations via subsidiaries in U.S. states. Moreover, some have subsidiaries for different products.

Having constructed these proxies, I run the regression specification,

$$\begin{aligned} \text{Share}_{ist} = & \sum_s \beta_s \, \mathbb{1}\{\text{Industry} = s\} \times \text{Liability risk}_{it} \\ & + \beta_{Missing} \text{ Liability risk}_{it} + \sum_s \gamma_s \, \mathbb{1}\{\text{Industry} = s\} \times \text{Log(Assets)}_{it} \\ & + \gamma_{Missing} \text{ Log(Assets)}_{it} + \boldsymbol{\delta X}_{it} + u_i + v_{st} + w_{ht} + \varepsilon_{ist}. \end{aligned} \tag{1.5.1}$$

Liability risk$_{it}$ is one of the variables described above by insurer i in year t. All other variables are defined as above. u_i, v_{st} and w_{ht} are insurer, industry-time and HQ location-time fixed effects.

Essentially, equation 1.5.1 derives for each industry the relationship between a risk factor and the share of an insurer's portfolio allocated to this industry, controlling for size. More specifically, the inclusion of the set of industry dummy interactions with *Log(Assets)*$_{it}$ ensures that I compare two insurers of the same size that differ in the geographic properties or the product structure of their underwriting business. The model prescribes that the relationship between *Liability risk*$_{it}$ is positive and significant for finance bonds in the case of the spatial (business) Herfindahl-Hirschman index and the spatial (business) concentration ratio. A larger Herfindahl-Hirschman index or concentration ratio implies that the insurer is more focused on certain geographies (products) and, hence, faces more volatility. In turn, the number of states (products) where an insurer writes premiums must be negatively related to the investments in finance bonds.

Panel 1 of Table 1.5.2 shows the estimates of equation 1.5.1 with the spatial risk factors. Columns (1) and (2) show the results for the *Spatial HHI*$_{it}$, columns (3) and (4) for the number of *Active states*$_{it}$, and columns (5) and (6) for the *Spatial concentration ratio*$_{it}$. Consistent with the predictions in the model, there

22. The 13 product categories I observe in the data are "Homeowners & Farmowners", "Private Auto", "Fire & Allied", "Commercial Multiple Peril", "Financial & Mortgage Guaranty", "Ocean & Inland Marine", "Medical Professional Liability", "Workers' Comp", "Other & Product Liability", "Commerical Auto", "Aircraft", "Fidelity & Surety", and "Other Commercial."

is a negative relationship between underwriting risk and the portfolio share of finance bonds. In the first (last) two columns, the coefficient is positive because a higher *Spatial* HHI_{it} (*Spatial concentration* $ratio_{it}$) corresponds to a higher geographic focus of the underwriting business, hence higher underwriting risk. In turn, the coefficient is negative in columns (3) and (4) because insurers are more diversified if they underwrite business in more states. The coefficient on the interaction terms of the risk factor and size always go in the opposite direction of the coefficient on the risk factor. This fact hints at a tradeoff between geographic diversification and size. However, the coefficients are only mildly significant and small.

Panel 2 shows the estimates of equation 1.5.1 with the business risk factors. Analogous to the spatial risk factors, there is a negative relationship between the business focus of insurers and the share of the corporate bond portfolio allocated to finance bonds. However, the coefficients on the risk factors interacted with industry dummies are only consistent for the *Active* $lines_{it}$ and only mildly significant or insignificant for the other two variables. Again, the results suggest a tradeoff between business diversification and size because the coefficients on the interaction term go in the opposite direction.

Table 1.5.2. Underwriting risk and finance bond investments

Panel 1: Geographic diversification

	Dependent variable: $Share_{ist}$					
Risk variable:	*Spatial* HHI_{it}		*Active* $States_{it}$		*Spatial conc.* $ratio_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Finance_s$ × Log(Assets)$_{it}$	-2.495***	-2.502***	-2.943***	-2.932***	-2.380***	-2.376***
	[-11.84]	[-11.77]	[-10.23]	[-9.86]	[-9.65]	[-9.53]
$Finance_s$ × Liability $risk_{it}$	0.114**	0.113**	-0.104**	-0.100**	0.129**	0.130**
	[2.31]	[2.20]	[-2.13]	[-1.99]	[2.41]	[2.35]
$Finance_s$ × Liability $risk_{it}$	-0.007*	-0.007*	0.006	0.005	-0.008*	-0.008*
× Log(Assets)$_{it}$	[-1.79]	[-1.73]	[1.47]	[1.37]	[-1.88]	[-1.85]
Other industries	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HQ Location-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	443,016	427,667	443,016	427,667	443,016	427,667
R^2	0.630	0.629	0.630	0.629	0.630	0.629
Adj. R^2	0.627	0.625	0.627	0.626	0.627	0.625

Table 1.5.2 continued.

Panel 2: Business diversification

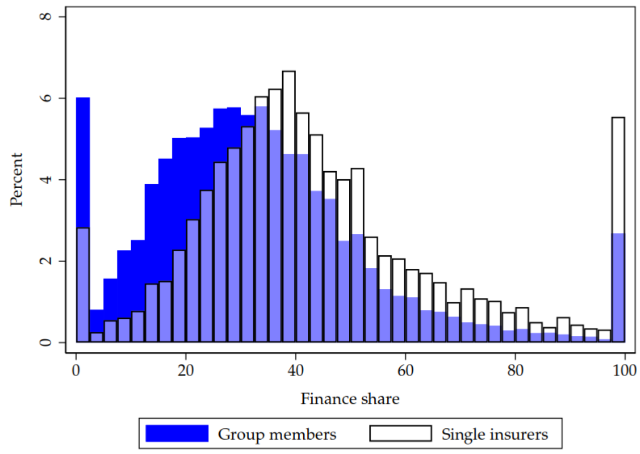
	Dependent variable: $Share_{ist}$					
Risk variable:	*Business HHI*$_{it}$		*Active lines*$_{it}$		*Business conc. ratio*$_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Finance}_s \times \text{Log(Assets)}_{it}$	-2.187***	-1.954***	-3.450***	-3.613***	-2.405***	-2.214***
	[-4.41]	[-3.91]	[-9.13]	[-8.92]	[-5.86]	[-5.37]
$\text{Finance}_s \times \text{Liability risk}_{it}$	0.128	0.177**	-0.253**	-0.284***	0.097	0.142*
	[1.46]	[1.96]	[-2.42]	[-2.65]	[1.29]	[1.84]
$\text{Finance}_s \times \text{Liability risk}_{it}$	-0.011	-0.016**	0.019**	0.022***	-0.009	-0.013**
$\times \text{Log(Assets)}_{it}$	[-1.58]	[-2.12]	[2.33]	[2.60]	[-1.41]	[-1.99]
Other industries	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HQ Location-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	365,797	356,363	365,797	356,363	365,797	356,363
R^2	0.621	0.621	0.621	0.621	0.621	0.621
Adj. R^2	0.618	0.617	0.618	0.617	0.618	0.617

Notes: This table provides estimates for the relationship between insurance companies' liability risk factors and insurers' portfolio share of Finance bonds. Panel 1 shows the results for three risk factors derived from the geographic properties of insurers' underwriting business; panel 2 shows the results for three risk factors derived from the allocation of premiums underwritten across types of insurance contracts. The dependent variable $Share_{ist}$ is the share of the corporate bond portfolio insurer i invests in corporate bonds from industry s at time t. $Log(Assets)_{it}$ is the natural logarithm of insurer i's total assets at time t. $Finance_s$ is an indicator variable that takes the value one if the dependent variable is the industry share of two-digit NAICS code 52, i.e., Finance. $Liability\ risk_{it}$ is a proxy for the liability risk of insurer i in the year t. The headings above the columns show which proxy is used in the regressions. I control for several financial variables of the insurer, i.e., *Leverage*, *ROE* and *RBC ratio*, portfolio characteristics, i.e., the *Portfolio HHI*, and the average rating of the industry sector, *Rating*. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

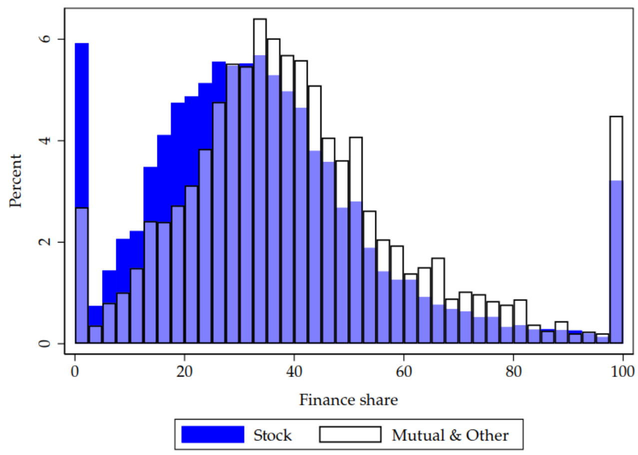
1.5.2 Group Membership and Organizational Structure

Consistent with Campello (2002), who documents the importance of financial conglomerates as capital providers to the individual subsidiaries, also insurance groups relax the financial constraints of their subsidiary insurers. For example, insurance groups act as internal capital markets (Ge (2022), Oh, Sen, and Tenekedjieva (2023)), relax capital constraints (Koijen and Yogo (2016)), or enhance risk sharing across lines of business and geographies. Hence, subsidiaries of an insurance group are less financially constrained than their independent counterparts (controlling for size). Besides relaxing financial constraints, insurance groups also relax the transaction cost contraints of their subsidiary insurers. Insurance groups pool their asset management resources and can thereby achieve lower transaction costs in corporate bond markets.[23] The purchased assets are then distributed via internal transfers. Overall, these effects should make subsidiaries of an insurance group less dependent on finance bonds. During the sample period, a substantial share of insurance companies, particularly smaller ones, were still operating independently (see Figure 1.D.7).

Figure 1.5.1. Insurance groups, stock companies, and finance investments



(a) Group membership



(b) Organizational structure

Notes: This figure shows the histograms of the distribution of insurers' Finance portfolio shares for (a) subsidiaries of insurance groups versus independent insurers and (b) stock companies versus mutual companies and others. The distribution is pooled over the entire sample period.

23. For example, the Metropolitan Group, better known as MetLife, consisted at the end of 2019 of 14 life and P&C insurers and reported more than $436 billion in assets to the NAIC. MetLife Investment Management, an asset management subsidiary of MetLife, manages major parts of these assets.

The organizational structure of an insurance company also matters for financial constraints. Most insurers are either organized as stock companies or mutual companies (see Figure 1.D.7). Stock insurers raise capital by issuing equity or bonds, while mutual insurers are limited to issuing surplus notes, i.e., mutual insurers have limited access to external finance compared to stock insurers. Hence, financial constraints for mutual insurers are more costly, and they should be more cautious about diversifying their asset side, i.e., using finance bonds.

Figure 1.5.1 shows that there are substantial differences in the portfolio share of finance bonds across both (a) group subsidiaries and independent insurers and (b) stock insurers and mutual companies. The distribution of the finance portfolio share of subsidiaries is shifted towards zero compared to the independent insurers. The differences become most visible at the extreme parts of the distribution. More than 5 percent of independent insurers barely keep any finance bonds in their portfolio, while only less than 2.5 percent of the independent insurers do so. On the other hand, more than 5 percent of independent insurers invest almost their entire corporate bond portfolio in finance bonds. However, less than 2.5 percent of subsidiaries rely entirely on finance bonds. The figure shows that the average independent insurer invests more in finance bonds than the average group subsidiary. A similar picture arises in comparing stock and mutual companies, albeit less pronounced.

In Table 1.E.9, I formally test the importance of access to external capital for insurers and estimate regression 1.5.1 but replace $\textit{Liability risk}_{it}$ with dummy variables $\textit{Group member}_{it}$ or $\textit{Stock}_{it}$. $\textit{Group member}_{it}$ ($\textit{Stock}_{it}$) takes the value one if insurer i was a member of an insurance group (was organized as a stock company) in year t. The results confirm the visual evidence of Figure 1.5.1. Panel 1 shows that finance bonds play a significantly smaller role in the portfolios of group subsidiaries. Moreover, the relationship between size and portfolio allocation to finance bonds is significantly weaker among group subsidiaries than independent insurers. Panel 2 provides similar results for the importance of the organizational structure. However, the coefficients on the interaction term between $\textit{Stock}_{it}$ and $\textit{Log(Assets)}_{it}$ are only significant at the 10% level or insignificant for finance bonds. The smaller and less significant effects in panel 2 can be due to the importance of agency costs for mutual companies. Stock companies are subject to regulations and have established internal control mechanisms that aim to minimize the agency costs that may arise from the separation of ownership, management, and control, i.e., the policyholders (see Jensen and Meckling (1976), Fama and Jensen (1983)).[24] Mutual insurers usually do not have a separation of ownership and control and often lack internal mechanisms to control the manager. The management

24. For an insurance-specific discussion of agency conflicts, see Mayers and Smith Jr. (1981) and Mayers and Smith Jr. (1988).

might exploit this discretion and not diversify enough. Hence, mutual insurers would tilt away from finance bonds.

1.6 Additional Evidence

In this section, I present additional evidence that aligns with the model's second and third prediction but offers less statistical significance. First, I exploit the regulatory fragmentation of U.S. insurance law to show that insurers more constrained in their price setting invest more in finance bonds. Second, I leverage transaction-level data on syndicated loans to measure the diversification of insurers' finance bond portfolios. On average, small insurers invest more in finance bonds issued by diversified financial institutions.

1.6.1 Regulatory Pricing Frictions

Insurance companies' first measure to manage the risk associated to their underwriting business by setting actuarially fair premiums on their policies. The premiums policyholders pay on their insurance should reflect the risk exposure associated with the contract. Insurers carry additional business risk if they cannot set prices to the actuarially fair value. In this case, insurers must be more careful with their asset investments because a devaluation of these investments would push them closer to default.

I exploit the institutional fragmentation of the U.S. insurance landscape to provide additional evidence for my main hypothesis. In the US, insurance companies have to ask regulators if they want to change the prices, conditions, or application forms of their insurance contracts. More specifically, as insurance regulation is subject to state law, an insurer has to submit a filing to the state regulator where the insurer would like to adjust the insurance product. Oh, Sen, and Tenekedjieva (2023) show that there is substantial heterogeneity in regulators' "leniency" across states. That results, for example, in multi-state insurers cross-subsidizing their homeowners insurance business in states that are strict on price requests by increasing prices more in states that are lenient. In the model context, this regulatory heterogeneity creates cross-sectional variation in the variance of insurers' underwriting liabilities, i.e., σ_L.

I have access to insurers' rate filings data via the S&P Insurance Product Filings database. The data contains all insurers' filings for any change to their insurance product. The most common requests are changes to the price (rate filing), the conditions (rule filing), or the application forms (form filing) of an insurance product. I observe when the filing was submitted, when the regulator made the final decision, and what the outcome of the decision was. For the rate filings, I additionally have information on the rate change targeted by the insurer and the rate change received after the decision by the regulator. I use this data to construct a measure of regulatory friction. I adapt the procedure of Oh, Sen, and Tenekedjieva (2023) and determine states' price-setting frictions. Analogous to their paper, I only consider rate filings and calculate the $Friction_f$ of a filing f as

$$\text{Friction}_f \;=\; 1 - \frac{\text{Rate}\Delta\text{Received}_f}{\text{Rate}\Delta\text{Target}_f}, \tag{1.6.1}$$

where $Rate\Delta Target_f$ is the target rate calculated by the insurer in filing f and $Rate\Delta Received_f$ is the rate accepted by the regulator in filing f. I winsorize the $Friction_f$ variable on the 1% and 99% levels. Then, I take for each state the average of $Friction_f$ over all filings that were issued in state s between 2010 and 2019. $Friction_s$ denotes this average for state s. To compute the average, I only consider filings where $Rate\Delta Received_f$ and $Rate\Delta Target_f$ have both been positive and $Rate\Delta Received_f$ has been lower or equal than $Rate\Delta Target_f$. First, this accounts for rate filings with a negative $Rate\Delta Target_f$ which should not be motivated by insurers' increased business risk. Second, a situation where $Rate\Delta Received_f$ is larger than $Rate\Delta Target_f$ is highly unlikely and, if so, does not show any friction at all. Finally, I classify states as high-friction, medium-friction, and low-friction states according to the terciles of $Friction_s$.

The main changes compared to Oh, Sen, and Tenekedjieva (2023) are the following. First, I consider all filings for price changes, not only for homeowners insurance product changes. Second, because I consider all P&C insurance products, I decrease the thresholds for insurers whose filings are included in calculating $Friction_s$. More specifically, I include all filings within a year where an insurer had an overall market share of at least 0.5% in the P&C business in at least 20 U.S. states. Market shares are defined as the share of P&C premiums written by an insurer in a state divided by total P&C premiums written in that state.[25]

In the second step, I take the state-level friction measure and match it to the data on premiums written (NAIC Schedule T). Then, I calculate several insurer-year-level friction measures. *High (Low)* $friction_{it}$ constitute insurer i's share of the business (in percentage points) conducted in high- (low-)friction states in year t. All variables are weighted by the share of premiums underwritten in state s by insurer i in year t over the total premiums underwritten by insurer i in year t.

If the hypothesis is true, insurers with a business focus in high (low) friction states invest relatively more (less) in finance bonds. To test this, I regress the share of the corporate bond portfolio invested in finance bonds on the pricing constraint variables, i.e.,

25. Oh, Sen, and Tenekedjieva (2023) calculate the measure based on insurers that had at least a 1% market share in the homeowners insurance line in all 51 U.S. states.

$$\begin{aligned}\text{Finance share}_{it} &= \beta_C \text{ Pricing constraint}_{it-1} + \beta_A \text{ Log(Assets)}_{it} \\ &+ \beta_{C\times A} \text{ Pricing constraint}_{it-1} \times \text{Log(Assets)}_{it} \\ &+ \gamma \boldsymbol{X}_{it} + u_i + v_t + \varepsilon_{it}.\end{aligned} \tag{1.6.2}$$

Pricing constraint$_{it}$ is one of the variables *High friction*$_{it}$, and *Low friction*$_{it}$ constructed above. All other variables are defined as above.

Table 1.6.1. Regulatory pricing constraints and finance share

	Dependent variable: *Finance share*$_{it}$					
Pricing constraint$_{it-1}$:	*High friction*$_{it-1}$			*Low friction*$_{it-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Pricing constraint$_{it-1}$	23.922**	21.736*	22.327*	-22.418	-23.765	-25.489*
	[2.10]	[1.85]	[1.92]	[-1.55]	[-1.64]	[-1.76]
Pricing constraint$_{it-1}$	-1.944**	-1.731*	-1.812*	1.834	1.936	2.116*
× Log(Assets)$_{it}$	[-2.04]	[-1.75]	[-1.84]	[1.45]	[1.52]	[1.67]
Log(Assets)$_{it}$	-2.311***	-3.336***	-3.064***	-3.511***	-4.518***	-4.309***
	[-2.67]	[-3.45]	[-3.12]	[-4.34]	[-4.90]	[-4.56]
Group member$_{it}$		-1.129	-0.613		-1.052	-0.544
		[-0.87]	[-0.47]		[-0.81]	[-0.42]
Controls	No	Yes	Yes	No	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
HQ Location-Time FE	No	No	Yes	No	No	Yes
No. of obs.	14,720	14,378	14,375	14,720	14,378	14,375
R^2	0.700	0.680	0.701	0.699	0.680	0.701
Adj. R^2	0.640	0.630	0.641	0.640	0.629	0.641

Notes: This table provides estimates for the relationship between insurers' regulatory pricing constraints and insurers' portfolio share of Finance bonds. The dependent variable *Finance share*$_{it}$ is the share of the corporate bond portfolio insurer i invests in Finance bonds at time t. *Pricing constraint*$_{it-1}$ is the proxy for the severity of pricing constraints insurer i faces at time $t-1$. The headings above the columns show which proxy is used in the regressions. *Log(Assets)*$_{it}$ is the natural logarithm of insurer i's total assets at time t. *Group member*$_{it}$ is an indicator variable that takes the value one if the insurer i has been part of an insurance group at time t. I control for several financial variables of the insurer, i.e., *Leverage*, *ROE* and *RBC ratio*, and portfolio characteristics, i.e., the *Portfolio HHI*. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

I expect β_C to be positive (negative) for *High friction*$_{it-1}$ (*Low friction*$_{it-1}$), and the coefficient $\beta_{C\times A}$ to go in the opposite direction. The reason is that insurers mainly operating in high-friction states face difficulties in managing their underwriting risk with rate adjustments and, hence, need to keep a more diversified portfolio. In contrast, insurers operating more in low-friction states do not have to worry as much. Table 1.6.1 shows the estimates for regression equation 1.6.2. The results confirm the hypothesis, albeit they are not significant. Insurers with a stronger business focus in high (low) friction states hold more (less) finance bonds on average. Moreover, the size-investment relationship is stronger (weaker) among insurers with a stronger business focus in high (low) friction states.

Most of the coefficients, however, are insignificant. The results from Oh, Sen, and Tenekedjieva (2023) might explain this fact. Insurance groups can cross-subsidize their business in high-friction states with business in low-friction states. Hence, insurance groups manage to mitigate the effect of the pricing constraint, and, in turn, the effect on the portfolio allocation is less pronounced among insurance group members. To test this presumption, I rerun regression 1.6.2 for the subsamples of independent insurers and insurance group members. The results are printed in Table 1.E.10. Independent insurers drive the relationship between pricing constraints and investments in finance bonds. The coefficients are larger in magnitude and significant, while the coefficients are small and insignificant for the subsample of group members. The results are consistent with the idea of cross-subsidization presented in Oh, Sen, and Tenekedjieva (2023) or the shadow insurance idea brought forward by Koijen and Yogo (2016).

1.6.2 Intermediated Diversification

In the model, the bank creates value for small insurers by maintaining a diversified portfolio.[26] However, if the bank invested in a concentrated portfolio, the bank bonds would be less valuable for small insurers. Hence, I expect that small insurers, relative to large insurers, invest in securities of more diversified issuers. Put differently, I expect the portfolio of finance bonds of small insurers to have a larger degree of diversification compared to the finance bonds of large insurers.

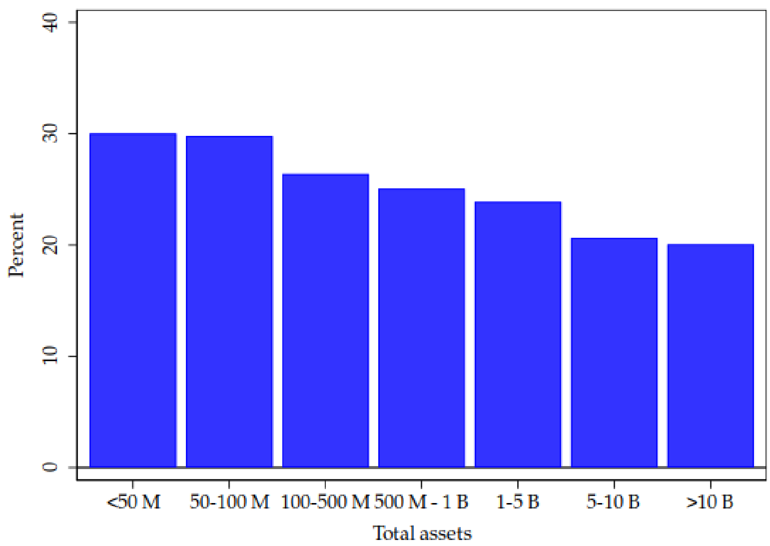
The challenge is to measure the degree of "intermediated diversification" of insurers' finance bonds. As a proxy, I will take the share of finance bonds issued by active lenders on the syndicated loan market. I define an active lender on the syndicated loan market as a financial institution with a loan portfolio of always greater than \$10 billion between 2010 and 2019. The syndicated loan market accounts for a large part of the overall U.S. loan market, and numerous studies use it to proxy for the U.S. corporate loan market.[27] The lenders in the syndicated loan market are large financial intermediaries that conduct corporate lending and many other financial activities. Hence, being an active lender on syndicated loan markets is a good proxy for the degree of financial intermediation. To determine whether an active DealScan lender issues a bond, I access the Compustat LoanConnector DealScan data set, which covers the syndicated loan market. With the DealScan data, I track lenders' loan portfolios over the sample period from 2010 to 2019. I aggregate lenders to the highest consolidation level, i.e., count subsidiaries' loan

26. In addition, the bank already creates value because of the equity it expects in period 1. Put differently, the bank creates value because of financial engineering.

27. See Ivashina and Scharfstein (2010), Chodorow-Reich (2014), Giannetti and Saidi (2019), Saidi and Žaldokas (2021) and others.

portfolios towards the loan portfolio of their parent company. Then, I define the indicator variable *Active lender*$_l$, which takes the value 1 if the lender l maintained a loan portfolio of at least \$10 billion over the entire sample period. I merge lender IDs from DealScan via Compustat with bond CUSIPs from Mergent FISD to merge the data with the insurer holdings. For a detailed description of the merging process, see section 1.B in the Online Appendix.

Figure 1.6.1. Diversification in the finance bond portfolio across size



Notes: This figure shows the average share of Finance bonds matched with DealScan across five different size buckets. The share is computed in terms of par value invested in the securities.

To finally measure the degree of intermediated diversification, I define *Share diversified lenders*$_{it}$ as the share of finance bonds insurer i invests in at time t issued by active lenders on the syndicated loan market. Consistent with the model, I predict that small insurers, on average, invest a larger share of their finance bonds in diversified lenders than their larger counterparts. Figure 1.6.1 provides preliminary evidence supporting this hypothesis. It shows the share of finance bonds invested in diversified lenders across the seven insurer size buckets. Small insurers invest a larger share of their finance bonds in issuers who are active lenders on the syndicated loan market. To formally test this hypothesis, I run the regression,

$$\text{Share diversified lenders}_{it} = \beta \text{ Log(Assets)}_{it} + \gamma \boldsymbol{X}_{it} + u_i + v_t + \varepsilon_{it}. \tag{1.6.3}$$

Share diversified lenders$_{it}$ is the diversification measure described above. I measure the share variable in terms of number of securities held or the par value invested. $\boldsymbol{X}_{it}$ is a vector of controls. All other variables are defined as above.

Table 1.6.2 provides the estimates for regression equation 1.6.3. The results confirm the hypothesis, albeit there is little significance. In columns (1) and (4), a negative relationship exists between size and how much insurers invest their finance bond portfolio in diversified financial institutions. This relationship exists for the number of securities held and the par value invested. If I use an indicator variable for size, $Large_{it}$ that takes the value 1 if insurer i is above the median in terms of size at time t, then the coefficient gets significant at the 5%-level. Although the results are less pronounced in terms of significance, they support the hypothesis of finance bonds as a diversification tool.

Table 1.6.2. Intermediated diversification and insurers' size

	Dependent variable: *Share diversified lenders*$_{it}$					
Share measured with:	# Securities			Par value		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Assets)$_{it}$	-0.788			-0.624		
	[-1.26]			[-0.95]		
Large$_{it}$		-1.798**	-1.893**		-2.047**	-2.173**
		[-1.99]	[-2.07]		[-2.07]	[-2.17]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
HQ Region-Year FE	No	No	Yes	No	No	Yes
No. of obs.	23,717	23,717	23,449	23,708	23,708	23,444
R squared	0.587	0.587	0.585	0.574	0.574	0.573
Adj. R squared	0.529	0.529	0.525	0.514	0.515	0.512

Notes: This table provides estimates for the relationship between the insurers' size and the degree of intermediated diversification. The dependent variable *Share diversified lenders*$_{it}$ is the share of Finance bonds insurer i invests in at time t that a financial institution issues flagged as an active lender on the syndicated loan market. The share is measured either in terms of number of securities held - columns (1) to (3) - or in terms of par value invested - columns (4) to (6). *Log(Assets)*$_{it}$ is the natural logarithm of insurer i's total assets at time t. Large$_{it}$ is an indicator variable that takes the value one if insurer i is above the median of the yearly cross-sectional distribution of the variable *Log(Assets)*$_{it}$ at time t. I control for several financial variables of the insurer, i.e., *ROE*, *RBC ratio*, and *Leverage*. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

1.7 Alternative Explanations

In this section, I rule out two other potential drivers of the size-investment relationship. First, I provide evidence that finance bonds are not cheaper in terms of liquidity costs than bonds of other industries, and, hence, insurers do not simply buy the cheapest bonds. Second, I show that the results are not driven by insurers' considerations to maintain a good relationship with the dealer.

1.7.1 Penny-Pinching Insurers

Instead of saving liquidity costs while maintaining diversification of the corporate bond portfolio, small and constrained insurers might buy finance bonds simply because they are the cheapest in terms of transaction costs. As described above, the corporate bond market is still highly illiquid despite advances in past years. Because smaller and more constrained insurers cannot afford large transaction costs, they might search for the cheapest bonds. In particular, small insurers face already higher transactions costs as small trades are relatively more expensive than large trades, and they usually do not have a large dealer network to get different price quotes (see Schultz (2001), Edwards, Harris, and Piwowar (2007), Harris (2015), Hendershott, Li, Livdan, and Schürhoff (2020), Pintér, Wang, and Zou (2021)). If finance bonds are the least expensive way to access the corporate bond market, then the previous results could be driven by the motivation to save on transaction costs.

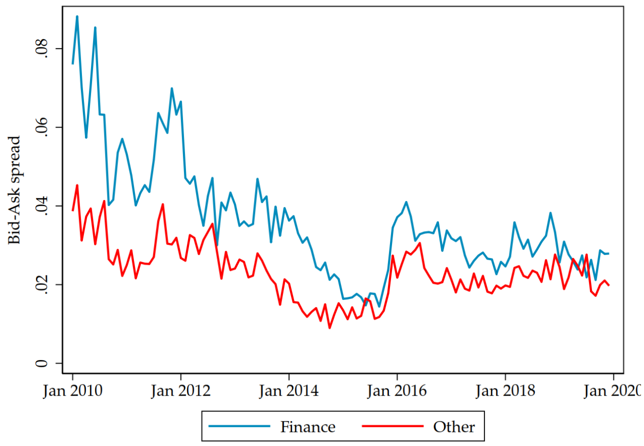
To address this concern, I impute trading costs across the different industries from transaction data in TRACE. First, I calculate monthly Bid-Ask spreads for all bonds I can match with Mergent FISD. The Bid-Ask spread gives information about the price spread between a bond's sale and buy transactions. A high Bid-Ask spread implies that the bond is costly to buy and cheap to sell. If small and constrained insurers are simply penny-pinching, then finance bonds should be among the bonds with the lowest Bid-Ask spreads. Figure 1.7.1 shows the time series of Bid-Ask spreads for the top-100 finance bonds and bonds of other industries in terms of liquidity. The figure shows that (the most liquid) finance bonds were not significantly cheaper in terms of transaction costs over the sample period. Shortly after the financial crisis, finance bonds were even considerably more expensive compared to bonds from other industries.

Because most cost-based liquidity measures suffer from the weakness that they can only be calculated if at least one buy and one sell trade occurred.[28] Figure 1.7.2 compares liquidity of finance bonds and bonds from other industries for small trade sizes over time. More specifically, the figure shows the number of nonzero trading days of non-finance bonds as a fraction of the number of nonzero trading days of finance bonds. I consider bonds among the least liquid in their industry, that is, the 25th percentile of the quarterly distribution. The trade sizes shown in Figure 1.7.2 are trade sizes a small insurer should aim for if the insurer would aim to build a diversified corporate bond portfolio. There are two important takeaways. First, bonds from other industries were always as liquid as finance bonds in small trade size classes. Second, the liquidity in other industries has

28. Schestag, Schuster, and Uhrig-Homburg (2016) extensively discuss the issue of measuring liquidity of corporate bonds from trading data.

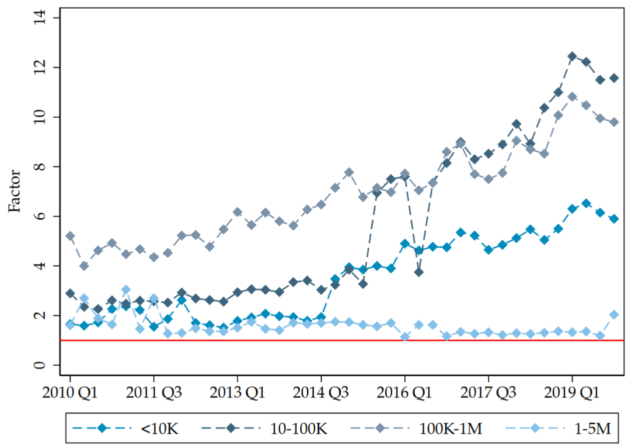
increased relative to finance bonds, in particular for trades below $100,000. In sum, these findings speak against the sole penny-pinching motive of insurers.

Figure 1.7.1. Trading costs of finance bonds versus other industries



Notes: This figure shows the time series of the mean Bid-Ask spread of the 100 most liquid Finance bonds versus the 100 most liquid bonds from all other industries. More specifically, the blue line plots for each month the mean Bid-Ask spread of the 100 Finance bonds with the lowest Bid-Ask spread in the respective month. The red line plots the mean Bid-Ask spread of the 100 bonds that had the lowest Bid-Ask spread in the respective month across all other industries.

Figure 1.7.2. Liquidity of finance bonds versus other industry sectors for small trade sizes



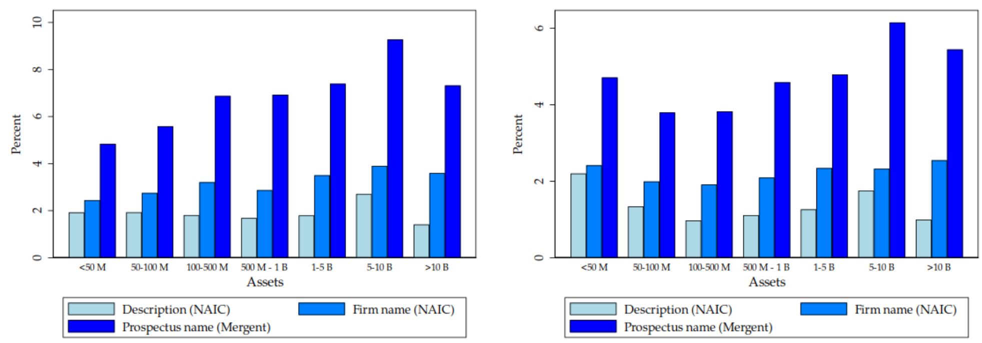
Notes: This figure plots the liquidity of Finance bonds compared to bonds from other industry sectors for small trade sizes over time. Each line represents one of the following trade sizes: trades with a par value lower than $10,000, trades between $10,000 and $100,000, trades between $100,000 and $1 million, and trades between $1 million and $5 million. The lines plot the ratio of the average of the 25th percentiles of the industry sector distributions of monthly nonzero trading days for all bonds that belong to the specific industry sector and the 25th percentile of the monthly distribution of nonzero trading days for all Finance bonds. The horizontal red line represents a ratio of 1, i.e., equal liquidity.

1.7.2 Keeping the Dealer Happy

The dealer-customer relationship is significant because of the over-the-counter structure of corporate bond markets. A relationship with a bond dealer is the golden ticket to the corporate bond market. Dealers might exploit this position and predominantly offer constrained investors their bonds or bonds issued by their affiliates. Alternatively, constrained investors might depend more on the relationship and hope to get more favorable conditions if they buy bonds issued by the dealer or one of its subsidiaries. As insurers report counterparties of their transactions, I can test whether the liability risk factors predict the counterparty of the insurer. More specifically, I create for each trade a variable that takes the value one if the traded bond has been issued by the dealer or one of its subsidiaries. To match the bond with the dealer, I have to apply string matching of the dealer's name and the name of the bond's issuer, which I obtain either from the NAIC data or Mergent FISD.[29]

Figure 1.7.3 shows the share of trades with finance bonds where the bond issuer was the same as the dealer or was part of the same company. The left-hand figure (a) does not suggest a relationship between size and the probability that an insurer buys a bond issued by the dealer (or its subsidiaries). In general, such trades happen in the fewest cases. The right-hand figure (b) shows that the same holds for insurers' sales of bonds.

Figure 1.7.3. Finance bonds as access to corporate bond markets



(a) Acquisitions **(b)** Disposals

Notes: This figure plots the share of (a) acquisitions and (b) disposals of Finance bonds for which the vendor (purchaser) was also the issuer of the traded bond across insurers' size. The share is weighted by the par value traded. Bonds and vendors (purchasers) are matched by string matching of the vendor reported by the insurer in NAIC Schedule D Part 3 (Part 4) and the prospectus issuer name given in Mergent FISD, the firm name reported by the insurer, or the description of the bond reported by the insurer. The issuer of a bond and the vendor (purchaser) are assumed to be the same if the matching ratio between the two strings is more than 0.75 (on a scale from 0 to 1).

29. For a detailed description of how I create the indicator variable, see Appendix 1.B.

In Table 1.7.1, I examine whether other liability risk factors or insurer financials determine whether an insurer buys bonds issued by its dealer. Only the coefficient on the RBC ratio is significant but virtually zero. Hence, I do not find evidence that the results might be driven by the wish of constrained insurers to maintain a good relationship with their dealer.

Table 1.7.1. Liability risk and insurers' choice of finance bonds

	Dependent variable: $\mathbb{1}\{Vendor_a = Issuer_a\}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Assets)$_{it(a)-1}$	-0.001							0.001
	[-0.45]							[0.19]
Spatial HHI$_{it(a)-1}$		-0.002						-0.001
		[-0.17]						[-0.10]
Group Member$_{it(a)-1}$			0.007					0.007
			[1.35]					[1.32]
Leverage$_{it(a)-1}$				-0.000*				-0.000
				[-1.67]				[-0.67]
ROE$_{it(a)-1}$					-0.000			-0.000
					[-0.57]			[-1.06]
RBC ratio$_{it(a)-1}$						0.000***		0.000***
						[3.12]		[2.64]
Portfolio HHI$_{it(a)-1}$							-0.000	-0.000
							[-0.86]	[-0.91]
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HQ Location-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	255,169	235,340	255,169	255,169	252,356	249,031	255,169	230,461
R^2	0.045	0.045	0.046	0.046	0.046	0.046	0.045	0.046
Adj. R^2	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.035

Notes: This table shows estimates for the relationship between a match of the issuer of the bond traded and the dealer and insurers' liability risk factors and financials. The dependent variable is an indicator variable that takes the value one if the name of the vendor reported by the insurer for acquisition a matches any prospectus issuer name from Mergent FISD of the bond traded in acquisition a, or any other bonds that were issued by entities that belong to the same company as the bond traded. To be considered a match, the matching ratio must be above 0.75. *Log(Assets)*$_{it(a)-1}$ is the natural logarithm of insurer i's total assets at the end of the previous year $t(a)-1$. *Spatial HHI*$_{it(a)-1}$ is the Herfindahl-Hirschman index of premiums written by insurer i in year $t(a)-1$ across all US states. *Group Member*$_{it(a)-1}$ is an indicator variable that takes the value one if insurer i was part of an insurance group in the previous year $t(a)-1$ that consisted of two or more insurers. *Leverage*$_{it(a)-1}$ is the leverage of insurer i at the end of year $t(a)-1$. *ROE*$_{it(a)-1}$ is the return on equity of insurer i at the end of year $t(a)-1$. *RBC ratio*$_{it(a)-1}$ is the risk-based capital ratio of insurer i at the end of year $t(a)-1$. *Portfolio HHI*$_{it(a)-1}$ is the Herfindahl-Hirschman index across industry holdings of insurer i's corporate bond portfolio at the end of year $t(a)-1$. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

1.8 Conclusion

In this paper, I show that bonds issued by financial institutions take a particular role in insurers' corporate bond portfolios. Small insurers predominantly focus their portfolio on a few securities of other financial institutions, while large insurers hold many securities from a broad range of industry sectors. Existing drivers like "reaching for yield" or a preference for liquidity fail to explain this investment behavior. However, finance bonds offer the lowest idiosyncratic risk among all corporate bonds. After a regulatory reform in 2017 that extended insurers' access to bond ETFs, a low-cost, diversified alternative, finance bonds have become less attractive for small insurers. I capture these facts in a model where small insurers' focus on finance bonds results from financial intermediaries' diversification role. I derive various predictions from the model about insurers' use of finance bonds. I take these predictions to the data and show that insurers' portfolio allocation to finance bonds correlates with determinants of their risk-taking ability, and small insurers invest in diversified financial intermediaries while large insurers invest in more specialized financial institutions. At last, I rule out alternative drivers like liquidity considerations and dealer-customer relationships.

The findings of this paper are the first evidence of investors acknowledging the value of financial institutions' diversification role. An empirical challenge in testing the value of intermediaries' diversification activity is to isolate this function from other functions performed by financial institutions, such as access to financial services and others. Insurers' activity on the corporate bond market provides a good setting to study the value of diversification because insurers are heterogeneous in their risk-taking ability and do not seek access to other financial services via the corporate bond market. Hence, my findings support Diamond (1984)'s seminal contribution that financial intermediaries' diversification role is valuable.

Moreover, my findings imply that insurance regulators should continue facilitating insurers' access to diversified products. Before the bond ETF reform, small insurers used finance bonds as a diversification tool. The financial crisis, however, has shown that some risks of financial institutions may be hidden. Hence, small insurers may invest in finance bonds unaware of the additional risks which insurers may want to avoid. As small- to medium-sized insurers represent an important part of insurance markets, and therefore, households' state-contingent wealth, their investment decisions may have real consequences.[30] With access to cheap and diversified products such as bond ETFs, regulators defuse a potential transmission channel of financial fragility.

At last, this paper's findings open several potential future research avenues. First, this paper focuses on the sample period from 2010 to 2019. However, in particular, the results of the bond ETF reform suggest that the ties were even more substantial around the time of the financial crisis. To analyze this transmission channel for a time of severe financial distress will be of interest to policymakers. Second, with a significant portion of small- to medium-sized institutional investors

30. For example, P&C insurers with assets below $500 million underwrite a third of all premiums in P&C products, see Figure 1.D.1.

also investing in bond ETFs, the ownership structure of corporate debt will change dramatically. Understanding the consequences of this development for financial markets and the real economy constitutes a fruitful lane for future research.

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Appendix 1.A Matching DealScan and NAIC Schedule D

To match the DealScan data with the NAIC Schedule D data, I access four data sources: LoanConnector DealScan, Compustat, Mergent FISD and NAIC Schedule D. Moreover, I have to use two linking files, the Compustat-DealScan link created by Chava and Roberts (2008) and the identifier link between DealScan Legacy and LoanConnector DealScan provided by WRDS.

In general, the matching procedure contains four steps. First, I use DealScan and construct from DealScan a data set that tracks the annual loan portfolio for each lender. With the help of the linking file created by Chava and Roberts (2008), I aggregate lenders to a parent level and calculate the variable $\textit{Active lender}_l$. Then, I match lenders with information on each lender's 6-digit CUSIP from Compustat. To match this data later with Mergent and ultimately with the NAIC data, I separately create a match between Compustat and Mergent using the 6-digit CUSIPs from Compustat and assigning all 6-digit CUSIPs in Mergent that belong to the same parent, the same Compustat identifier. This allows me to match the NAIC data with Compustat identifiers, aggregate it to the parent level, and eventually match it with the diversification measure $\textit{Active lender}_l$. In the following, I will describe this process in more detail.

Step 1. I take the Compustat-DealScan linking database Chava and Roberts (2008) in order to later link the diversification variables via Compustat - which contains the lenders' 6-digit CUSIPs - and Mergent FISD - which contains the 9-digit securities issued by the companies - to the NAIC data. As the Compustat-DealScan linking table is only for the old LPC version of DealScan, I match the old DealScan IDs with the new LoanConnector IDs with the help of the linking table provided by WRDS Dealscan[31] This first step yields a mapping from Compustat *gvkey* identifiers to new LoanConnector DealScan identifiers.

Step 2. Next, I take the new Compustat LoanConnector Database from WRDS and match it with the linking table created in the first step. I match on the DealScan parent company identifier *Lender_Parent_Id* and, if not available, on the entity identifier *Lender_Id*.[32] This allows me to aggregate loan portfolios to the highest possible level of consolidation via Compustat's *gvkey*. For example, consider Wells Fargo, a large bank holding company with several subsidiaries such as Wachovia Bank[33] being active on the syndicated loan market. With the help of Compustat, I count all of these subsidiaries' loan portfolios towards the aggregate loan portfolio of Wells Fargo.

31. See WRDS Overview on DealScan.
32. If a lender has multiple *gvkeys* in Compustat, I take the most common one.
33. Wachovia Bank was acquired by Wells Fargo during the global financial crisis and integrated into Wells Fargo.

More specifically, I calculate for each year the amount of newly issued/bought loan tranches and the amount of matured loan tranches of a lender. Moreover, I calculate the stock of a lender's active loan tranches at the beginning of 2001 by summing all loans that were issued before 2001 and did not mature up to this point. Finally, I have a lender-year data set from 2001 to 2020, where a lender is the holding company.

Step 3. Now I need to create a match between Compustat's *gvkey* identifiers and the corporate bonds contained in Mergent FISD. From Compustat, I take the first six digits of the company's stock CUSIP. Usually, the first six digits of the CUSIP identify the issuer of a security, and all bonds and other securities issued by this company vary in the last three digits. As financial companies, however, issue a lot of different bonds and securities, they have multiple 6-digit CUSIPs. To account for this, I exploit the *parent_id* variable in Mergent FISD, a Mergent-specific identification number of the ultimate parent of the entity that issued the security. With the help of this variable, I assign each security with the same parent ID, the same *gvkey* from Compustat, if at least one of the 6-digit CUSIPs of all securities within the same group is merged with a 6-digit CUSIP from Compustat. This gives me a final linking table that matches 6-digit CUSIPs from Mergent to Compustat's *gvkey*, which allows me to link DealScan with the NAIC data.

Step 4. Finally, I track insurers' annual investments in all companies I manage to match with the Compustat-Mergent linking table created in the previous step. With the help of the end-of-year holdings data, I track insurance companies' holdings and aggregate them to a parent level via the Mergent-Compustat link. This final data set consists of an insurer-company-year level data set that shows the par value invested by insurer i in any security issued by firm f or one of f's subsidiaries at quarter t. Now, I can merge it with the diversification measure constructed from DealScan and calculate the share of Finance bonds issued by a diversified financial institution.

Appendix 1.B Matching Bonds and Dealers

To see whether the dealer issued the bond traded, I use two data sources: acquisitions and disposal data from NAIC Schedule D Part 3 and 4 and issue-level information from Mergent FISD. The NAIC transactions data contains all types of acquisitions and disposals of insurance companies, i.e., the data also contains bond maturities, bond calls, tax-free exchanges of bonds between insurers, and others. I can differentiate market transactions from other changes in the corporate bond portfolio with the help of the counterparty reported by the insurance company. For acquisitions, insurers have to report a "vendor" while they have to report a "purchaser" for disposals. These data fields are reported as strings and contain entries like "MATURED", "CALLED AT 100", and "TAX-FREE EXCHANGE" for non-market transactions. For market transactions, the insurer reports the name of the counterparty like "DEUTSCHE BANK", "JP MORGAN", and "GOLDMAN SACHS". In a first step, I filter out all market transactions. For this, I build a dictionary with keywords that fit market transactions, e.g., the names of large banks and financial counterparties.[34] Then, I match this data with issue-level information from Mergent FISD. To identify a bond-dealer match, I exploit three different sources of information. Each time, I use a fuzzy string matching method to find similarities between the "vendor" and "purchaser" variables in the NAIC data and one of the following three variables: (1) the variable "description" in the NAIC data which is a description of the security transacted by the insurer, (2) the variable "firm name" in the NAIC data which is the firm name of the issuer of the security transacted and reported by the insurer, and (3) the variable "prospectus name" in Mergent FISD which is the name of the issuer reported in the prospectus of a bond issue. I set the matching ratio of the fuzzy string matching to 0.75, that is, the similarity between the variable "vendor" ("purchaser") and the matching variable has to be at least 75 percent to be identified as a match. Figure 1.D.9, however, shows that the results of Figure 1.7.3 are robust to other matching thresholds like 0.5 (panel (a) and (b)) and 0.25 (panel (c) and (d)).

34. Previous work by Becker, Opp, and Saidi (2022) and Kubitza (2023) is gratefully acknowledged.

Appendix 1.C Data and Variable Definitions

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

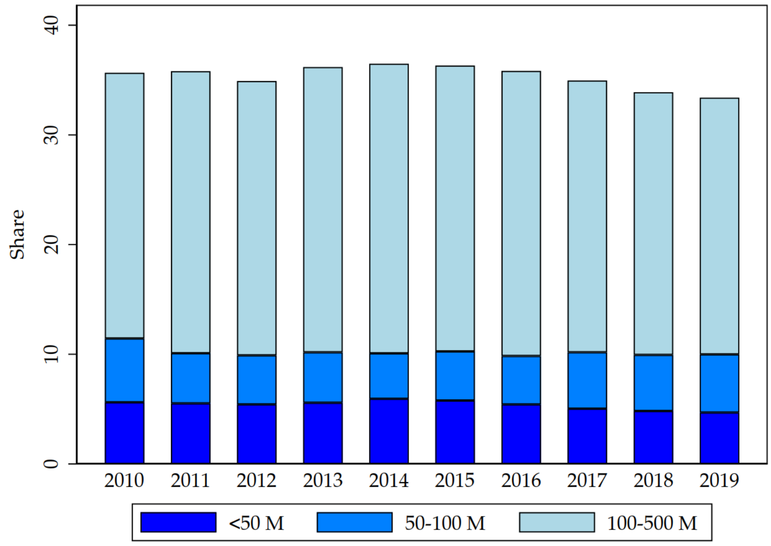
Variable	Definition (Unit)
	Insurer-level variables
Share	Share of the corporate bond portfolio invested in bonds from each NAICS sector at the end of the year. *Source: NAIC & Mergent FISD.*
Assets	Total assets at the end of the year. *Source: NAIC.*
Log(Assets)	The natural logarithm of the total assets reported by the insurer at the end of the year. *Source: NAIC.*
RBC ratio	The risk-based capital ratio reported by the insurer at the end of the year. *Source: NAIC.*
ROE	Annual return on equity. *Source: NAIC.*
Leverage	Leverage at the end of the year. *Source: NAIC.*
Portfolio HHI	Herfindhal-Hirschman index across sector shares of the corporate bond portfolio, i.e., across variable *Share*. *Source: NAIC & Mergent FISD.*
Spatial HHI	Herfindhal-Hirschman index across premiums written in U.S. states (US territories excluded). *Source: NAIC.*
Active states	Number of US states (US territories excluded) with positive premiums written. *Source: NAIC.*
Spatial concentration ratio	Share of premiums written in the state with the largest amount of premiums written. *Source: NAIC.*
Business HHI	Herfindhal-Hirschman index across premiums written in product lines. *Source: NAIC.*
Active lines	Number of product lines (US territories excluded) with positive premiums written. *Source: NAIC.*
Business concentration ratio	Share of total premiums written in the product line with the largest amount of premiums written. *Source: NAIC.*
Group member	An indicator variable that takes the value one if the insurer is part of an insurance group at the end of the year. *Source: NAIC.*
Stock	An indicator variable that takes the value one if the insurer is organized as a stock company. *Source: NAIC.*
Share diversified lenders	Share of Finance bonds invested in lenders that are sufficiently active on syndicated loan markets. *Source: NAIC, Mergent FISD & Compustat.*

Table 1.C.1 continued.

	Bond-level variables
Share issue	The share of a bond issue acquired by insurers of a certain size. *Source: Mergent FISD & NAIC.*
Liquidity at issuance	Bid-Ask spread in the year of issuance. *Source: Mergent FISD & TRACE.*
Issuance amount	The issue's offering amount. *Source: Mergent FISD.*
Log(Issuance amount)	The natural logarithm of the amount issued. *Source: Mergent FISD.*
Treasury spread	The difference between the bond's offering yield and a maturity-matched Treasury yield. *Source: Mergent FISD & U.S. Department of the Treasury.*
Time to maturity	Number of days from day of issuance to day of maturity. *Source: Mergent FISD.*
Active lender	An indicator variable that takes the value one if the bond was issued by a financial institution that always maintained a loan portfolio larger than $10 billion over the sample period 2010 to 2019. *Source: Mergent FISD & Compustat.*
	Firm-level variables
Company leverage	A firm's total liabilities divided by total assets. *Source: Compustat.*
EBIT margin	A firm's EBIT divided by total gross profit. *Source: Compustat.*
Cash balance	A firm's cash holdings divided by total assets. *Source: Compustat.*
	Sector-level variables
Sector rating	The average industry sector credit rating at the end of each year. *Source: Mergent FISD.*
Finance	An indicator variable that takes the value one if the bond is issued by a financial institution, i.e., an entity with two-digit NAICS code 52. *Source: Mergent FISD.*

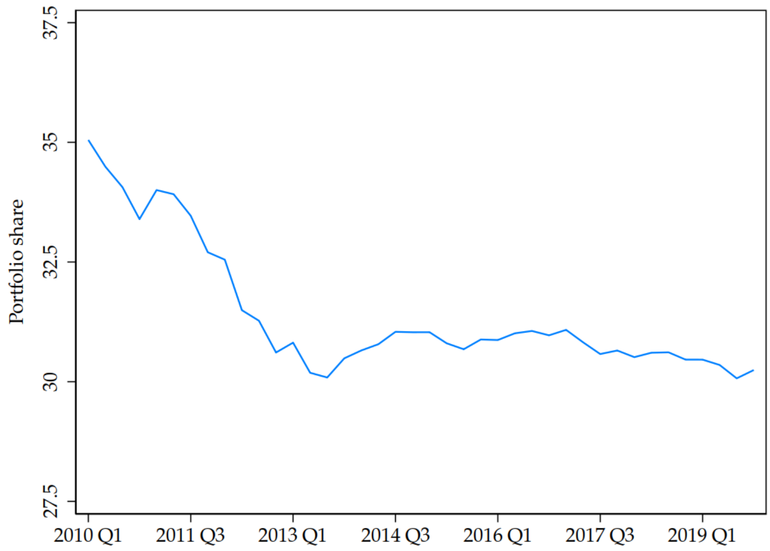
Appendix 1.D Additional Figures

Figure 1.D.1. Small- and medium-sized P&C insurers' market share over time



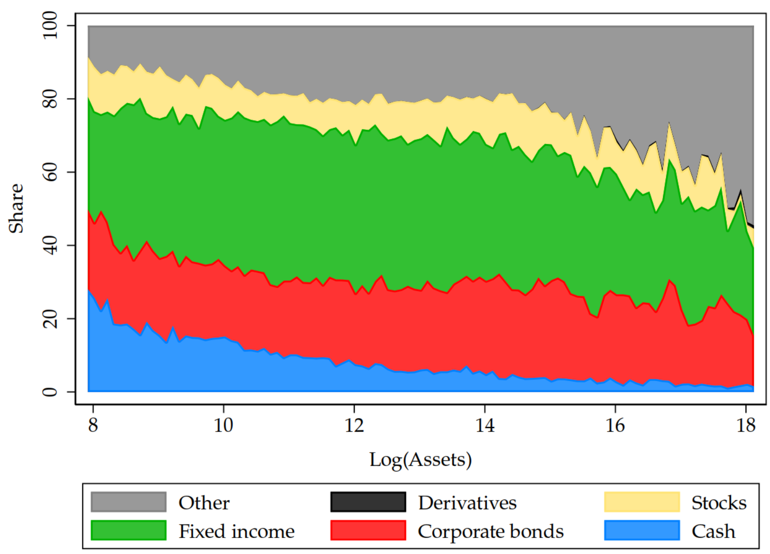
Notes: This figure plots the share of premiums written by P&C insurers with total assets of below \$50 million, \$50-100 million, and \$100-500 million.

Figure 1.D.2. Finance bonds in the market portfolio



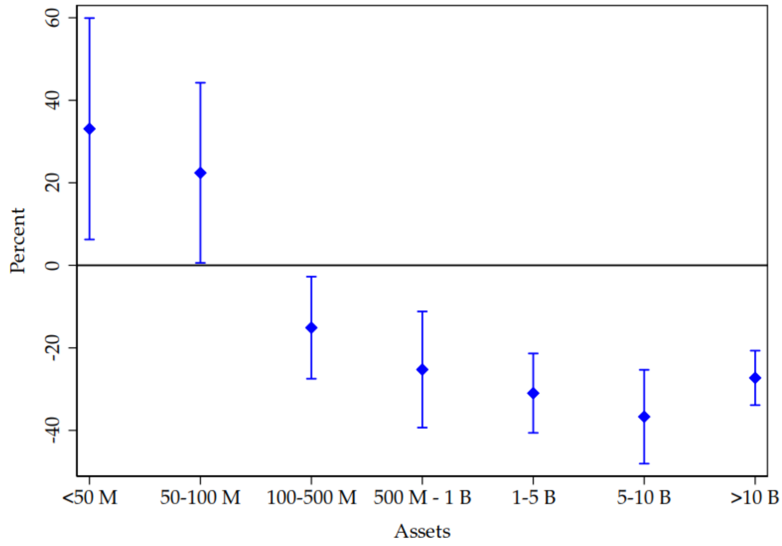
Notes: This figure plots the share of Finance bonds in the market portfolio over time. The market portfolio contains all active bonds from Mergent FISD that appear in at least one trade in TRACE Enhanced. Outstanding amounts are proxied by the offering amounts from Mergent FISD.

Figure 1.D.3. Insurers' size and asset side composition



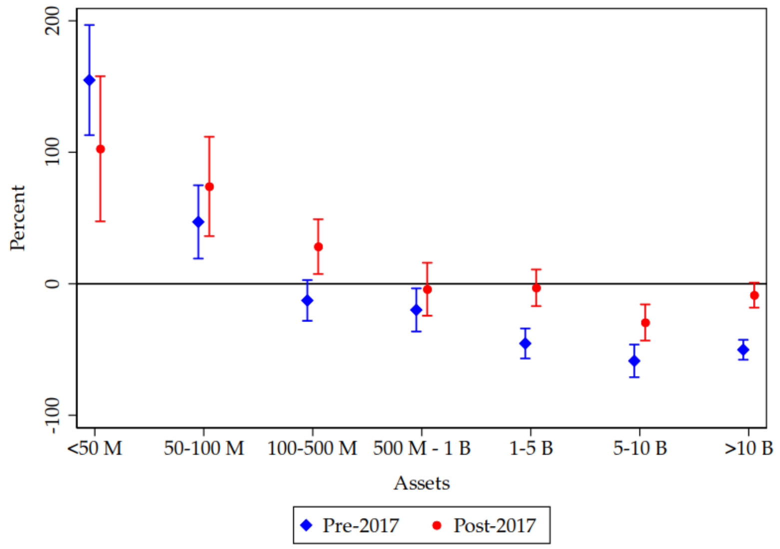
Notes: This figure plots asset side composition across insurers' size. It shows the share of insurers' total assets invested in cash (blue), corporate bonds (red), other fixed income securities like treasuries, MBS, etc. (green), equities (yellow), derivatives (black), and other assets like amounts recoverable from reinsurance agreements, or uncollected premiums. All units are measured at reported book value divided by total assets.

Figure 1.D.4. Insurers' overinvestment in finance bonds across size



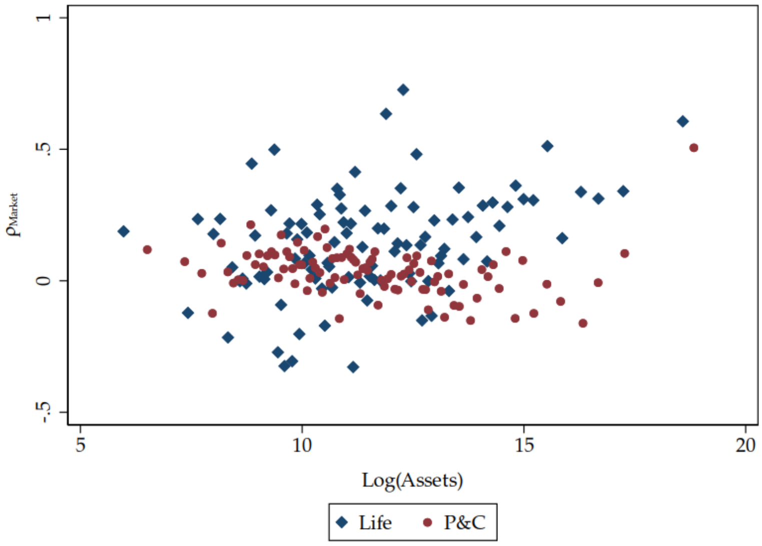
Notes: This figure plots the estimates for the β coefficients of equation 1.2.2 for each of the seven different size buckets scaled by the mean of the dependent variable. The caps represent the 95% confidence intervals. Standard errors are clustered at the issuer level.

Figure 1.D.5. Robustness: Impact of the 2017 NAIC bond ETF reform on the use of finance bonds



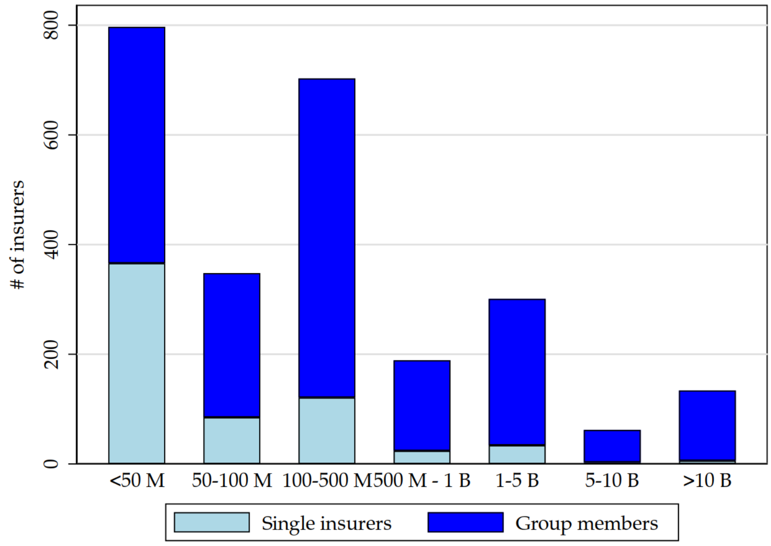
Notes: This figure plots the β coefficients of regression 1.3.1 for the seven different size buckets scaled by mean of the dependent variable. It replicates the approach from Becker, Opp, and Saidi (2022) and considers only new issues proxied for by insurers' year-end holdings in the year of issuance. It includes all years of the sample period.

Figure 1.D.6. Correlation of liability side and market risk factor across size

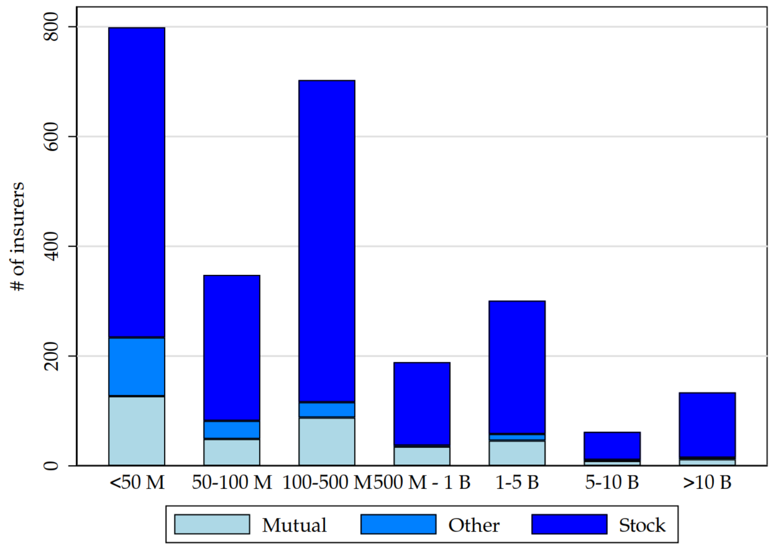


Notes: This figure plots the correlation coefficients of annual percent changes in insurers' total liabilities reported to the NAIC and the market risk factor taken from Fama and French (1993).

Figure 1.D.7. Group membership and organizational structure



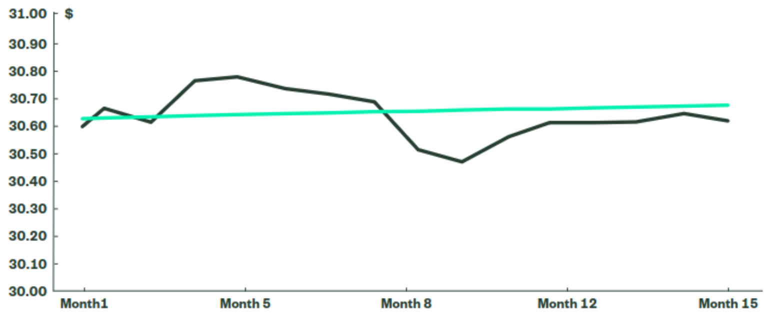
(a) Group membership



(b) Organizational structure

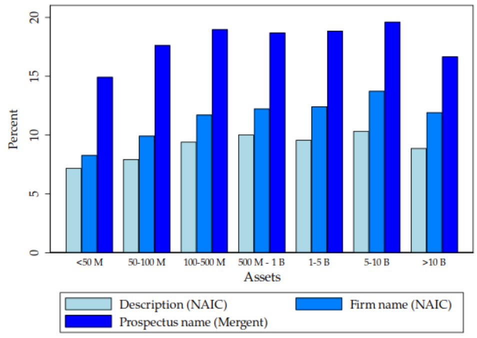
Notes: This figure shows (a) the number of independent insurers compared to the number of group subsidiaries and (b) the number of mutual and other insurers compared to the number of stock insurers across seven size buckets at the end of 2016.

Figure 1.D.8. Systematic value versus NAV

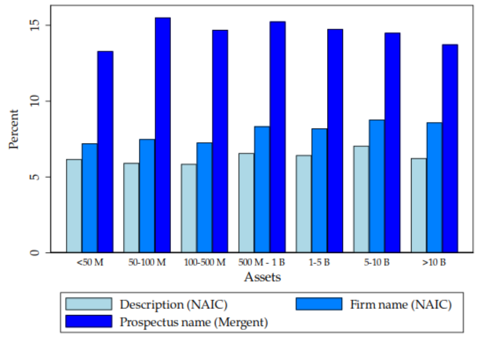


Notes: This figure plots the book value of an ETF share in the case of the systematic value approach (black) and the fair value approach (green). Source: State Street Global Advisors (2021).

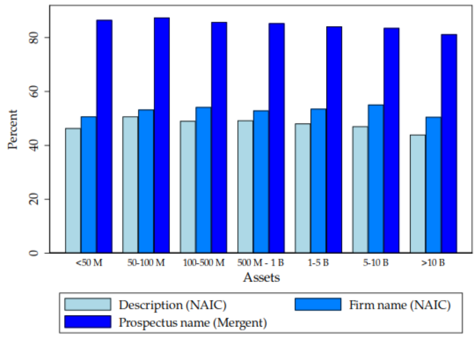
Figure 1.D.9. Robustness: Finance bonds as access to corporate bond markets



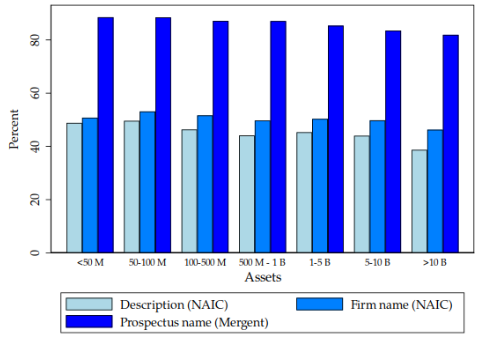
(a) Acquisitions - matching ratio 0.5



(b) Sales - matching ratio 0.5



(c) Acquisitions - matching ratio 0.25



(d) Sales - matching ratio 0.25

Notes: This figure plots the share of acquisitions (lefthand-side figures) and disposals (righthand-side figure) of Finance bonds for which the vendor (purchaser) was also the issuer of the traded bond across insurers' size. The share is weighted by the par value traded. Bonds and vendors (purchasers) are matched by string matching of the vendor reported by the insurer in NAIC Schedule D Part 3 (Part 4) and the prospectus issuer name given in Mergent FISD, the firm name reported by the insurer, or the description of the bond reported by the insurer. The issuer of a bond and the vendor (purchaser) are assumed to be the same if the matching ratio between the two strings is more than 0.5 in panels (a) and (b) and more than 0.25 in panels (c) and (d) (on a scale from 0 to 1).

Appendix 1.E Additional Tables

Table 1.E.1. Further information on the sample

No. of insurers	
Minimum	2,567
Maximum	2,681
By insurance line	
P&C	1,998
Life	628
Insurer-year pairs	26,270
No. of observations	551,670

Notes: This table shows information on the main sample regarding the number of insurers, insurer-year pairs, and the number of observations.

Table 1.E.2. The size-investment relationship in the fixed income portfolio

	Dependent variable: $\frac{Par\ value_{ist}}{Item_{it}}$					
$Item_{it}$:	$Total\ bonds_{it}$		$Total\ invested\ assets_{it}$		$Total\ assets_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Finance_s	-0.954***	-0.954***	-0.469***	-0.469***	-0.527***	-0.527***
$\times$ Log(Assets)_{it}	[-12.23]	[-12.23]	[-9.06]	[-9.06]	[-11.08]	[-11.08]
Log(Assets)_{it}	0.105***	0.105***	0.079***	0.079***	0.043**	0.043**
	[4.22]	[4.22]	[3.65]	[3.65]	[2.32]	[2.32]
Other industries	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
HQ Location-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	544,395	544,395	544,395	544,395	544,395	544,395
R^2	0.544	0.544	0.529	0.529	0.532	0.532
Adj. R^2	0.540	0.540	0.526	0.526	0.528	0.528

Notes: This table provides estimates for the relationship between insurance companies' size and insurers' share of assets invested in Finance bonds. In columns (1) and (2), the dependent variable is the share of all fixed income assets insurer *i* invests in corporate bonds from industry *s* at time *t*. In columns (3) and (4), the dependent variable is the share of all invested assets insurer *i* invests in corporate bonds from industry *s* at time *t*. In columns (5) and (6), the dependent variable is the share of all assets insurer *i* invests in corporate bonds from industry *s* at time *t*. $Log(Assets)_{it}$ is the natural logarithm of insurer *i*'s total assets at time *t*. $Finance_s$ is a dummy variable that takes the value one if the dependent variable is the industry share of two-digit NAICS code 52, i.e., Finance. I control for several financial variables of the insurer, i.e., *Leverage*, *ROE* and *RBC ratio*, portfolio characteristics, i.e., the *Portfolio HHI*, and the average rating of the industry sector, *Rating*. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 1.E.3. Summary statistics for the issue-level sample

Panel 1: Issue-level information

	Number of bonds in sample: 17,406						
	Mean	SD	1st	25th	Median	75th	99th
***Share issue* of insurers**							
with *Assets* <$ 50M	0.07	0.31	0.00	0.00	0.00	0.04	2.36
with *Assets* $ 50-100M	0.08	0.22	0.00	0.00	0.00	0.06	1.50
with *Assets* $ 100-500M	0.56	1.05	0.00	0.00	0.15	0.70	6.21
with *Assets* $ 500 M - 1 B	0.39	0.75	0.00	0.00	0.09	0.49	4.00
with *Assets* $ 1 B - 5 B	1.98	2.98	0.00	0.16	0.84	2.67	14.59
with *Assets* $ 5 B - 10 B	1.00	1.68	0.00	0.00	0.35	1.25	8.31
with *Assets* $ > 10 B	11.19	13.80	0.00	1.37	6.09	15.45	58.93
Issuance amount ($ mn)	729.87	4,684.52	2.55	300.00	500.00	850.00	3,000.00
Liquidity at issuance	0.33	0.55	-0.36	0.09	0.18	0.34	3.07
Finance	0.27	0.44	0.00	0.00	0.00	1.00	1.00
Yield spread	244.15	207.59	35.00	100.00	165.00	325.00	918.00
Time to maturity	7.30	4.16	1.32	4.50	6.95	9.42	28.39
Rating	12.33	6.56	2.00	7.00	10.00	16.00	23.00
Enhancement	0.25	0.43	0.00	0.00	0.00	1.00	1.00
Asset backed	0.00	0.05	0.00	0.00	0.00	0.00	0.00
Rule 144A	0.36	0.48	0.00	0.00	0.00	1.00	1.00

Panel 2: Idiosyncratic risk variables

	Number of bonds in sample: 29,200						
	Mean	SD	1st	25th	Median	75th	99th
Fama-French 3-factor	2.37	2.14	0.14	1.18	1.82	2.74	13.92
Enhanced Fama-French	2.20	2.07	0.00	1.07	1.68	2.54	13.59

Notes: This table shows the summary statistics for the issue-level sample. Panel 1 shows the summary statistics for issue-level information, and panel 2 shows the estimated idiosyncratic risk variables. *Share issue* is the share of the bond issue acquired by insurers with *Assets* in one of the seven different size buckets. *Issuance amount ($ mn)* is the offering amount of the bond issue reported in Mergent FISD. *Liquidity at issuance* is the mean Bid-Ask spread of the issue in the year of issuance. *Finance* is an indicator variable that takes the value one if the bond was issued by a Finance entity, i.e., an issuer with a two-digit NAICS code of 52. *Yield spread* is the difference between the issue's offering yield reported in Mergent and a maturity-matched Treasury bond. *Time to maturity* is the issue's number of days from the issue date to the maturity date. *Rating* is the credit rating at the time of issuance. *Enhancement* is an indicator variable that takes the value one if the bond issue has an enhancement option. *Asset backed* is an indicator variable that takes the value one if the bond issue is asset-backed. *Rule 144A* is an indicator variable that takes the value one if the bond issue is a rule 144A bond. *Fama-French 3-factor* is the variance of estimated residuals from a Fama and French (1993) 3-factor model. *Enhanced Fama-French* is the variance of estimated residuals from a Fama and French (1993) 3-factor model enhanced with the liquidity factor from Dick-Nielsen (2009) and the TED spread.

Table 1.E.4. Insurers' size, finance bonds, and investments

	Dependent variable: *Share issue*$_{b;k}$						
Insurers:	\$<50M	\$50-100M	\$100-500M	\$500M-1B	\$1-5B	\$5-10B	\$>10 B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Finance$_b$	0.025**	0.017**	-0.085**	-0.099***	-0.612***	-0.368***	-3.053***
	[2.42]	[2.01]	[-2.40]	[-3.52]	[-6.31]	[-6.32]	[-8.09]
Yield spread$_b$	-0.000***	-0.000***	-0.001***	-0.001***	-0.004***	-0.001***	-0.016***
	[-5.00]	[-7.48]	[-9.18]	[-6.85]	[-8.52]	[-7.22]	[-11.57]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity-Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	8,323	8,323	8,323	8,323	8,323	8,323	8,323
R^2	0.241	0.110	0.146	0.117	0.207	0.209	0.435
Adj. R^2	0.232	0.099	0.137	0.106	0.198	0.200	0.428

Notes: This table provides estimates of regression equation 1.2.2. The dependent variable *Share issue*$_{b;k}$ is the share of the new issue b acquired by insurers with total assets in size bucket k. *Finance*$_b$ is an indicator variable that takes the value one if a financial institution has issued the bond b. *Yield spread*$_b$ is the spread between the offering yield reported in Mergent and a maturity-matched Treasury yield. I control for several additional issue-level characteristics, i.e., *Liquidity at issuance*, *Market portfolio share*, *Time to maturity*, and indicator variables for enhancement, asset-backed and rule 144A bonds. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 1.E.5. Robustness I: Insurers' size, finance bonds, and investments

	Dependent variable: *Share issue*$_{b;k}$					
Specification:	Baseline		+Firm controls & HQ FE		+HQ-Year FE	
Insurers:	$<50M	$50-100M	$<50M	$50-100M	$<50M	$50-100M
	(1)	(2)	(3)	(4)	(5)	(6)
Finance$_b$	0.025**	0.017**	0.038***	0.038***	0.048***	0.044***
	[2.42]	[2.01]	[3.33]	[3.71]	[3.98]	[4.07]
Yield spread$_b$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[-5.00]	[-7.48]	[-3.76]	[-5.85]	[-4.04]	[-5.89]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Maturity-Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
HQ State FE	No	No	Yes	Yes	No	No
HQ State-Year FE	No	No	No	No	Yes	Yes
No. of obs.	8,323	8,323	4,844	4,844	4,799	4,799
R^2	0.241	0.110	0.242	0.129	0.269	0.172
Adj. R^2	0.232	0.099	0.220	0.104	0.200	0.094

Notes: This table provides estimates of regression equation 1.2.2. The dependent variable *Share issue*$_{b;k}$ is the share of the new issue b acquired by insurers with total assets in size bucket k. *Finance*$_b$ is an indicator variable that takes the value one if a financial institution has issued the bond b. *Yield spread*$_b$ is the spread between the offering yield reported in Mergent and a maturity-matched Treasury yield. I control for several additional issue-level characteristics, i.e., *Liquidity at issuance*, *Market portfolio share*, *Time to maturity*, and indicator variables for enhancement, asset-backed and rule 144A bonds. Additionally, I control for several firm-level characteristics in columns (3) to (6). The firm-level controls are the *Company Leverage*, the *EBIT margin*, and the *Cash balance* and are taken from Compustat. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 1.E.6. Robustness II: Insurers' size, finance bonds, and investments

	Dependent variable: *Share issue*$_{bkt}$						
Insurers:	\$<50M	\$50-100M	\$100-500M	\$500M-1B	\$1-5B	\$5-10B	\$>10B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Finance$_b$	0.029***	0.021*	-0.048	-0.085**	-0.507***	-0.366***	-2.680***
	[2.59]	[1.82]	[-1.00]	[-2.12]	[-3.75]	[-4.27]	[-5.05]
Yield spread$_b$	-0.000***	-0.000***	-0.002***	-0.001***	-0.005***	-0.001***	-0.015***
	[-3.21]	[-5.23]	[-6.12]	[-5.31]	[-6.59]	[-4.31]	[-6.53]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity-Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	4,200	4,200	4,200	4,200	4,200	4,200	4,200
R^2	0.267	0.101	0.106	0.095	0.167	0.167	0.386
Adj. R^2	0.254	0.086	0.091	0.079	0.153	0.153	0.376

Notes: This table provides estimates of regression equation 1.2.2 for a sample of matched bonds. The matching procedure consists of two steps. In the first step, Finance bonds are matched with non-Finance bonds on the maturity buckets, credit ratings, and issuance year. Then, I apply a propensity score matching method with the other covariates below. The dependent variable *Share issue*$_{b;k}$ is the share of the new issue *b* acquired by insurers with total assets in size bucket *k*. *Finance*$_b$ is an indicator variable that takes the value one if a financial institution has issued the bond *b*. *Yield spread*$_b$ is the spread between the offering yield reported in Mergent and a maturity-matched Treasury yield. I control for several additional issue-level characteristics, i.e., *Liquidity at issuance*, *Market portfolio share*, *Time to maturity*, and indicator variables for enhancement, asset-backed and rule 144A bonds. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 1.E.7. Robustness I: Idiosyncratic risk of finance versus other bonds

	Dependent variable: $\sigma(\hat{\varepsilon})_b$						
			Quintiles of *Issuance amount*$_b$				
			1st	2nd	3rd	4th	5th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Finance$_b$	-0.115***	-0.128***	0.902***	0.893***	-0.191	-0.087	-0.242***
	[-3.18]	[-3.34]	[5.29]	[4.74]	[-1.61]	[-1.18]	[-5.38]
Liquidity at issuance$_b$	0.274***	0.275***	0.228***	0.104	0.281***	0.722***	0.244**
	[7.93]	[7.84]	[3.23]	[1.15]	[3.59]	[5.32]	[2.10]
Log(Issuance amount)$_b$	0.076***	0.067***	0.468***	0.350*	-0.122	0.031	0.201***
	[3.90]	[3.38]	[2.77]	[1.67]	[-0.95]	[0.12]	[3.29]
Issue Year-Maturity-Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issue Year-SIFI FE	No	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	6,032	6,026	274	287	1,270	1,320	2,447
R^2	0.365	0.369	0.451	0.582	0.326	0.491	0.509
Adj. R^2	0.331	0.333	0.386	0.527	0.196	0.411	0.461

Notes: This table shows estimates for regression equation 1.2.5. The sample comes from a mixed matching procedure. In the first step, Finance bonds are matched to non-Finance bonds with exact matching on the following characteristics: credit rating at issuance, maturity bucket, quintile of the cross-sectional distribution of issuance size, quintile of the cross-sectional distribution of liquidity, and year of issuance. Within an exact matching, I apply a propensity score matching method based on the *Liquidity at issuance* and *Log(Issuance amount)*. The dependent variable $\sigma(\hat{\varepsilon})_b$ is the variance of residuals estimated from five-factor models, that is, the Fama-French three-factor model combined with the liquidity factor developed by Dick-Nielsen, Feldhütter, and Lando (2012), and the TED spread. *Finance*$_b$ is an indicator variable that takes the value one if a financial institution has issued the bond *b*. *Liquidity at issuance*$_b$ is the average Bid-Ask spread in the year of issuance of bond *b*. *Log(Issuance amount)*$_b$ is the natural logarithm of the amount issued of bond *b*. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 1.E.8. Robustness II: Idiosyncratic risk of finance versus other bonds

	Dependent variable: $\sigma(\hat{\varepsilon})_b$						
			Quintiles of *Issuance amount*$_b$				
			1st	2nd	3rd	4th	5th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Finance$_b$	-0.069*	-0.109***	-0.232	0.910***	-0.323***	-0.111	-0.202***
	[-1.82]	[-2.72]	[-0.86]	[4.19]	[-2.66]	[-1.42]	[-4.16]
Liquidity at issuance$_b$	0.231***	0.224***	0.159***	0.164***	0.165***	0.666***	0.221**
	[10.17]	[9.82]	[3.35]	[3.68]	[3.55]	[5.85]	[2.17]
Log(Issuance amount)$_b$	0.058***	0.056***	0.375***	0.260**	-0.149	-0.116	0.163***
	[4.22]	[4.00]	[2.63]	[1.97]	[-1.58]	[-0.51]	[2.77]
Issue Year-Maturity-Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issue Year-SIFI FE	No	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	9,178	9,176	568	743	2,270	1,671	3,705
R^2	0.372	0.375	0.384	0.576	0.362	0.449	0.506
Adj. R^2	0.343	0.345	0.284	0.517	0.263	0.360	0.461

Notes: This table shows estimates for regression equation 1.2.5. The sample comes from a mixed matching procedure. In the first step, Finance bonds are matched to non-Finance bonds with exact matching on the following matching characteristics: quintile of the cross-sectional distribution of issuance size, quintile of the cross-sectional distribution of liquidity, and year of issuance. Within an exact matching, I apply a propensity score matching method based on the *Liquidity at issuance* and *Log(Issuance amount)*. The dependent variable $\sigma(\hat{\varepsilon})_b$ is the variance of residuals estimated from Fama-French three-factor models. *Finance*$_b$ is an indicator variable that takes the value one if a financial institution has issued the bond *b*. *Liquidity at issuance*$_b$ is the average Bid-Ask spread in the year of issuance of bond *b*. *Log(Issuance amount)*$_b$ is the natural logarithm of the amount issued of bond *b*. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 1.E.9. Access to external finance and finance bond investments

Panel 1: Group membership

	Dependent variable: $Share_{ist}$			
	(1)	(2)	(3)	(4)
$Finance_s$ × $Log(Assets)_{it}$	-3.043***	-3.054***	-3.055***	-3.055***
	[-8.86]	[-8.59]	[-8.58]	[-8.58]
$Finance_s$ × Group $Member_{it}$	-16.319***	-16.263***	-16.271***	-16.271***
	[-3.70]	[-3.57]	[-3.57]	[-3.57]
$Finance_s$ × Group $Member_{it}$ × $Log(Assets)_{it}$	0.811**	0.795**	0.796**	0.796**
	[2.19]	[2.08]	[2.08]	[2.08]
Other industries	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	No
Industry-Time FE	Yes	Yes	Yes	Yes
Insurer-Time FE	No	No	No	Yes
HQ Location-Time FE	No	No	No	Yes
No. of obs.	544,152	526,533	526,450	526,449
R^2	0.627	0.627	0.627	0.627
Adj. R^2	0.624	0.625	0.624	0.608

Panel 2: Organizational structure

	Dependent variable: $Share_{ist}$			
	(1)	(2)	(3)	(4)
$Finance_s$ × $Log(Assets)_{it}$	-3.240***	-3.178***	-3.137***	-3.128***
	[-11.15]	[-10.58]	[-10.09]	[-10.08]
$Finance_s$ × $Stock_{it}$	-11.899***	-10.574**	-9.908**	-9.815**
	[-2.95]	[-2.54]	[-2.29]	[-2.27]
$Finance_s$ × $Stock_{it}$ × $Log(Assets)_{it}$	0.617*	0.503	0.462	0.453
	[1.91]	[1.51]	[1.34]	[1.32]
Other industries	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	No
Industry-Time FE	Yes	Yes	Yes	Yes
Insurer-Time FE	No	No	No	Yes
HQ Location-Time FE	No	No	No	Yes
No. of obs.	551,670	532,959	526,730	526,449
R^2	0.625	0.625	0.625	0.625
Adj. R^2	0.622	0.623	0.622	0.605

Notes: This table provides estimates for the relationship between insurance companies' access to external finance and insurers' portfolio share of Finance bonds. Panel 1 proxies access to external finance with a dummy variable *Group member*$_{it}$ that takes the value one if insurer *i* is part of an insurance group in year *t*; panel 2 uses the dummy variable *Stock*$_{it}$ that takes the value one if insurer *i* was a stock company in year *t*. The dependent variable *Share*$_{ist}$ is the share of the corporate bond portfolio insurer *i* invests in corporate bonds from industry *s* at time *t*. *Log(Assets)*$_{it}$ is the natural logarithm of insurer *i*'s total assets at time *t*. *Finance*$_s$ is a dummy variable that takes the value one if the dependent variable is the industry share of two-digit NAICS code 52, i.e., Finance. I control for several financial variables of the insurer, i.e., *Leverage*, *ROE* and *RBC ratio*, portfolio characteristics, i.e., the *Portfolio HHI*, and the average rating of the industry sector, *Rating*. Standard errors are clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 1.E.10. Group membership, pricing frictions, and the use of finance bonds

	Dependent variable: *Finance share*$_{it}$			
Sample:	Single insurers		Group members	
	(1)	(2)	(3)	(4)
High friction$_{it}$	65.362***		9.014	
	[3.12]		[0.62]	
High friction$_{it}$ × Log(Assets)$_{it}$	-5.699***		-0.709	
	[-3.00]		[-0.59]	
Low friction$_{it}$		-59.029*		-11.922
		[-1.95]		[-0.72]
Low friction$_{it}$ × Log(Assets)$_{it}$		5.514**		0.958
		[2.04]		[0.67]
Log(Assets)$_{it}$	-1.263	-4.540*	-2.710**	-3.228***
	[-0.55]	[-1.89]	[-2.34]	[-2.96]
Controls	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
HQ Location-Time FE	Yes	Yes	Yes	Yes
No. of obs.	3,555	3,555	10,706	10,706
R^2	0.782	0.782	0.682	0.682
Adj. R^2	0.702	0.701	0.613	0.613

Notes: This table provides estimates for the relationship between insurers' regulatory pricing constraints and insurers' portfolio share of Finance bonds for the subsamples of independent insurers and insurance group members. The dependent variable *Finance share*$_{it}$ is the share of the corporate bond portfolio insurer i invests in Finance bonds at time t. *Pricing constraint*$_{it-1}$ is the proxy for the severity of pricing constraints insurer i faces at time $t-1$. The headings above the columns show which proxy is used in the regressions. *Log(Assets)*$_{it}$ is the natural logarithm of insurer i's total assets at time t. I control for several financial variables of the insurer, i.e., *Leverage*, *ROE* and *RBC ratio*, and portfolio characteristics, i.e., the *Portfolio HHI*. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

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Chapter 2

The Insurance Channel of Monetary Policy

Joint with Christian Kubitza and Jakob Ahm Sørensen

2.1 Introduction

The transmission of monetary policy through financial intermediaries is a long-standing topic in financial economics. While an extensive literature documents the transmission through banks (e.g., Drechsler, Savov, and Schnabl, 2017), much less is known about the role of insurance companies despite their importance as financial intermediaries. Insurance is not only a prerequisite for obtaining a mortgage or operating a vehicle, it also safeguards against the rising costs of health risks and natural disasters. The U.S. insurance sector collects insurance premiums of nearly $2 trillion from households annually and manages $8.5 trillion in financial assets corresponding to more than one-third of the banking sector's financial assets.[1] Insurance companies are, thus, pivotal in intermediating between financial markets and households.

In this paper, we document that monetary policy affects insurance markets through regulatory frictions, focusing on homeowners insurance. We find that insurance prices increase in response to rate hikes because insurers seek to compensate for the adverse impact of higher interest rates on their financial investments. Higher rates reduce insurers' net worth by depressing the market value of their

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1. Sources: NAIC Market Share Reports, NAIC Capital Markets Bureau Special Reports, and FRED.

assets, such as bonds, which tightens their regulatory capital constraints. Insurers (partly) restore regulatory capital by raising insurance prices to dampen this effect. Consistent with this regulation channel, we document that insurers respond significantly more to monetary policy shocks when they face tighter regulatory constraints ex-ante and hold assets with a longer duration (which are more interest rate sensitive) and at market value instead of historical cost. Finally, we provide evidence that homeowners insurance companies transmit monetary policy shocks to the broader economy. U.S. states where insurers are more exposed to monetary policy experience larger declines in home prices in response to rate hikes. Thus, insurance companies amplify the impact of monetary policy on residential real estate, the most important asset on U.S. households' balance sheets. This finding also suggests important effects on loan demand and, thus, spillover effects on the banking sector.

To guide the empirical analysis, we study a simple model of insurance markets. In a frictionless market, higher interest rates *reduce* insurance prices by lowering the present value of expected future claims. However, the higher interest rates also tighten statutory capital requirements by depressing the market value of insurers' financial assets. Consequently, insurers face a trade-off after an interest rate hike: increase insurance prices to ease regulatory constraints or lower insurance prices to boost demand in light of the lower present value of expected claims. The net effect hinges on two key factors observable in our data: (1) the interest rate sensitivity of insurers' financial assets, which determines how much an interest rate hike will tighten regulatory constraints, and (2) the insurers' pre-existing financial constraints, as *ex-ante* constrained insurers have to adjust prices more in order to mitigate the impact of an interest rate hike.

Our main analysis builds on novel data on U.S. homeowners insurance prices. Homeowners insurance protects policyholders from liability and physical damages, e.g., due to hurricanes, hail, or lightning. Banks generally require homeowners insurance to qualify for a mortgage, and premiums amount to approximately 20% of annual principal and interest payments (Keys and Mulder, 2024). Therefore, homeowners insurance is a significant cost component of homeownership and the first line of defense against climate risk exposure. As mounting losses from natural disasters have slashed the supply of homeowners insurance in recent years (Sastry, Sen, and Tenekedjieva, 2023), it is important to understand the supply frictions in this market and their interaction with financial conditions such as monetary policy.

We combine data on all individual changes in homeowners insurance prices in the U.S. since 2009 (at the insurer and state level) with granular information on property insurance companies' balance sheets. This provides a holistic view of prices and quantities in the insurance market and their relation to insurers' investment behavior. Monetary policy is endogenous to the macroeconomic environment. For example, a weak economy may prompt policymakers to loosen monetary policy and, at the same time, may dampen insurance demand. Therefore, correlating insurance prices with low-frequency monetary policy indicators, such as the level of the federal funds rate, likely provides a biased estimate of the causal impact of monetary policy. To overcome this challenge, we follow the macroeconomic literature and identify unexpected changes ("surprises") in the Fed's monetary policy stance by focusing on high-frequency variation in market interest rates in a narrow time window around monetary policy events (Bauer and Swanson, 2023). These high-frequency monetary policy surprises isolate market responses to unexpected monetary policy decisions *conditional* on the macroeconomic state of the economy. In line with the duration of insurers' financial investments, our baseline results use high-frequency surprises in the 10-year Treasury yield.

We find that insurers respond to contractionary monetary policy surprises by raising insurance prices. A 25 basis points (bps) monetary policy surprise in the six months prior to a price adjustment is associated with an additional insurance price increase of 1.5 percentage points (ppt). This result is robust across alternative definitions of monetary policy surprises (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018) and it also holds when controlling for various insurer characteristics (including lagged return on equity and leverage) as well as state-level macroeconomic conditions (including inflation, income, and GDP). The effect applies almost exclusively at the intensive margin, whereas insurance price adjustments occur nearly mechanically every year.

Our model predicts that insurance prices increase with rate hikes because these tighten regulatory frictions through their impact on insurers' investment income. We provide empirical evidence for this mechanism by exploiting variation in insurers' exposure to monetary policy shocks. First, we examine the pass-through of monetary policy to insurers' financial investments. Changes in insurers' statutory investment income directly affect their regulatory capital: we estimate that an additional $1 in investment income nearly entirely passes through to regulatory capital (after including insurer and time fixed effects). However, asset price changes do not entirely pass through to insurers' investment income. Investment income dynamics differ between assets held at market value and those held at historical cost. In particular, stocks and high-yield bonds are held at market value and, jointly, account for approximately 30% of invested assets and 40% of investment income. The negative impact of contractionary monetary policy shocks on these assets' prices entirely passes through to their investment income. Instead, investment-grade bonds (accounting for over 50% of invested assets) are held at historical cost; therefore, the income from holding these assets is insulated from asset price fluctuations. Nonetheless, insurers effectively re-value investment-grade bonds at market value when these are sold. In this case, insurers realize the difference in the purchase price as investment income, which accounts for 5% of total investment income. Thus, the pass-through of monetary policy to investment income depends on the share of stocks and high-yield bond investments and the share of investment-grade bonds sold.

For an average insurer, we document that the investment income significantly decreases in response to contractionary monetary policy surprises. We decompose this effect based on the underlying investments. A large part of this effect (80%) is driven by income from stock investments, consistent with the significant impact of monetary policy on stock market valuations (Chava and Hsu, 2020; Bauer and Swanson, 2023) and the fact that stocks are held at market value. In addition, the impact on income from holding high-yield bonds explains 8.5% of the total effect, whereas that from selling bonds explains 3%.

To provide further evidence of the impact of monetary policy on investment income as a key mechanism, we compute the interest rate duration of insurers' fixed-income investments. This measure reflects the sensitivity of an asset's market value to changes in interest rates. We aggregate the security-level duration at the insurer level, using information on each insurer's lagged portfolio holdings. We document that insurers with a longer (lagged) portfolio duration experience significantly larger declines in their investment income in response to contractionary monetary policy shocks. This effect is driven by investment income on bonds, but not stocks, which is consistent with the construction of the duration measure. Moreover, the impact of monetary policy on insurers' income from *selling* bonds is driven by insurers that face a low (or negative) free cash flow from underwriting business relative to their cash holdings. This finding suggests that insurers realize market value losses by selling bonds due to liquidity needs while avoiding these otherwise.

Second, we explore variation in insurers' regulatory capital ratio, comparing an insurer's capital ratio to its trailing moving average. A large negative deviation indicates an unusually low capitalization and, thus, proximity to regulatory thresholds.[2] We document that such regulatory-constrained insurers drive the response of insurance prices to monetary policy. The most constrained insurers raise prices significantly more than the least constrained insurers. This result also holds *within* state-by-month buckets, i.e., it reflects differences in the cross-section of insurers rather than the correlation between regulatory constraints and monetary policy over time.

Third, we show that regulatory constraints interact with the negative impact of monetary policy on investment income. We use a long duration and significant share of assets held at market value as indicators for insurers' investment exposure to monetary policy. We find that regulatory-constrained insurers raise prices significantly more when their investment income is more exposed. Moreover, the

2. U.S. insurance regulation prescribes minimum thresholds for risk-based capital ratios. Insurers that breach these thresholds face increased scrutiny by regulators. In the most extreme case, state insurance commissioners are required to take control of an insurer.

marginal impact of regulatory constraints on the response of insurance prices significantly strengthens with a larger investment income exposure. This latter result is robust to controlling for granular insurance product-by-state-by-month fixed effects. Thus, it cannot be explained by co-movement of investment strategies with monetary policy but, instead, reflects differences *across* insurers setting the price for similar products in the same state and within the same month.

Finally, we document the consequences of the insurance channel of monetary policy for the residential real estate market. Because U.S. insurance companies sell products at the state level, we focus on variation in the insurance sector's monetary policy sensitivity across states. From our most saturated regression specification, we predict the insurer-specific monetary policy sensitivity of insurance prices based on variation in lagged regulatory constraints and either the bond portfolio duration or the share of assets held at market value. We take the occurrence of product (re-)pricing as given (as it is uncorrelated with monetary policy surprises) and compute the average monetary policy sensitivity at the state level weighted by the total lagged insurance premiums affected by product repricing.

Building on county-level data on home prices, we document that the impact of monetary policy on home prices significantly depends on the balance sheets of local insurance companies. In counties exposed to more monetary-policy-sensitive insurance companies, home prices fall significantly more in response to contractionary monetary policy surprises than in other counties. This result holds when measuring insurers' sensitivity based on regulatory constraints and either bond duration or the share of assets that are marked to market (MTM). It is also robust to absorbing potentially confounding variation at the aggregate level, such as macroeconomic conditions' impact on insurers and real estate. Moreover, the differential impact on home prices is particularly large in locations with large average insurance premiums, reflected in large exposure to natural disasters, highlighting homeowners' vulnerability to the costs of insuring their homes in the presence of accelerating climate risks.

Our findings reveal that insurance markets play a dual role in transmitting monetary policy. On the one hand, insurance prices increase in response to contractionary monetary policy, which puts upward pressure on inflation. On the other hand, higher insurance prices reduce real estate demand and, therefore, depress residential real estate prices. Due to the importance of houses on U.S. households' balance sheets, higher insurance prices hence reduce household borrowing capacity, which likely has feedback effects in other markets. The importance of regulatory constraints for the pass-through of monetary policy to insurance prices suggests that the role of insurance markets is countercyclical: in economic downturns, insurers are particularly constrained and, thus, especially sensitive to monetary policy.

Related literature. The literature on the role of financial intermediaries in monetary policy transmission has traditionally focused on banks (e.g., Bernanke and Gertler, 1995). The mechanism through which monetary policy transmits to the insurance sector is most closely related to the balance sheet channel in banking, which posits that contractionary monetary policy shocks affect credit supply by reducing balance sheet strength (Stein, 1998; Kashyap and Stein, 2000; Jiménez, Ongena, Peydró, and Saurina, 2012; Bittner, Bonfim, Heider, Saidi, Schepens, et al., 2022). We show that a similar channel operates in the insurance sector as monetary policy weakens insurers' balance sheets, reducing insurance supply. Thereby, we also extend recent studies on monetary policy transmission through non-bank financial intermediaries, which have primarily focused on capital markets (Elliott, Meisenzahl, Peydro, and Turner, 2019; Xiao, 2020; Drechsler, Savov, and Schnabl, 2022).

An important challenge in the banking literature is distinguishing the balance sheet channel from other economic mechanisms. For this purpose, studies typically rely on cross-sectional differences in banks' equity ratio (e.g., in Bittner et al., 2022). Instead, we show that heterogeneity in investment strategies affects the pass-through of monetary policy to insurers' balance sheets, which provides a well-suited laboratory to study balance sheet frictions.

Existing evidence on the impact of monetary policy on insurance markets is scarce and primarily focuses on insurers' asset investments. Prior studies document the impact of monetary policy and, more broadly, market interest rates on insurance companies' asset demand (Ozdagli and Wang, 2019; Koijen, Koulischer, Nguyen, and Yogo, 2021; Kaufmann, Leyva, and Storz, 2023) and the duration of life insurance liabilities (Kubitza, Grochola, and Gründl, 2023). We contribute to these studies by focusing on the impact of monetary policy on insurance supply and its pass-through to housing markets.

The insurance literature has traditionally focused on informational frictions in insurance markets (Rothschild and Stiglitz, 1976) and only recently highlights the importance of financial frictions and market power (Koijen and Yogo, 2015; Koijen and Yogo, 2016; Koijen and Yogo, 2022; Oh, Sen, and Tenekedjieva, 2023). We extend this literature by documenting the role of balance sheet frictions in transmitting monetary policy to insurance markets. By focusing on the interaction between insurers' asset investments and regulatory constraints, we complement Knox and Sørensen (2024), who explore the role of (long-term) investment returns for insurance prices. We highlight differences in the pass-through of monetary policy across asset investments depending on their regulatory treatment and, therefore, complement the results of (Ellul, Jotikasthira, and Lundblad, 2011; Ellul, Jotikasthira, Lundblad, and Wang, 2015; Becker, Opp, and Saidi, 2022), who show that such differences affect insurers' investment behavior.

Finally, we contribute to the literature on the determinants of home prices. Kuttner (2013), Williams (2015), and Gorea, Kryvtsov, and Kudlyak (2023) explore the impact of monetary policy on home prices in the aggregate. We document significant cross-sectional heterogeneity depending on the state of local insurance markets. Thereby, we add to the growing literature on the role of insurance supply for real estate markets. Differences in insurance coverage against floods supplied by the U.S. National Flood Insurance Program affect home prices and mortgage supply (Blickle and Santos, 2022; Sastry, 2022; Ge, Lam, and Lewis, 2023). Sastry, Sen, and Tenekedjieva (2023) document the role of insurer counterparty risk for mortgage markets. Eastman, Kim, and Zhou (2024) find a negative correlation between homeowners insurance prices and home prices in Florida. Extending these studies, we provide empirical evidence for the causal impact of homeowners insurance supply on home prices, driven by the interaction between financial frictions in insurance markets and monetary policy. This evidence suggests a novel "insurance channel" of monetary policy transmission to households.

2.2 Institutional Setting and Stylized Facts

Homeowners insurance is one of the most important products for households in the U.S.; Jeziorski and Ramnath (2021) report that 94% of U.S. homeowners had insurance coverage in 2017. An important reason is that homeowners insurance is mandatory to obtain a mortgage. In addition, nearly 90% of non-mortgaged homeowners have an insurance policy (Jeziorski and Ramnath, 2021). There are eight types of homeowners insurance policies, called HO-1 to HO-8, which vary in coverage and policyholder group. HO-3 is the most common policy, which covers damages related to home and belongings, such as the costs of fixing broken pipes, damages caused by extreme weather events, and fire damages.[3] Only certain risks like flooding and wildfires may be excluded and require additional insurance protection.[4] Homeowners insurance premiums account for a substantial part of the housing costs, particularly for mortgage-financed home purchases.[5] Keys and Mulder (2024) estimate that homeowners insurance premiums are on average 20% of a mortgage's principal and interest payment; Oh, Sen, and Tenekedjieva (2023) report that, in the most expensive states, annual premiums may exceed interest payments.

3. In 2021, HO-3 policies represented more than 50% of homeowners insurance markets and more than 75% of policies for owner-occupied homes (National Association of Insurance Commissioners, 2023a).

4. Homeowners insurance typically excludes damages resulting from floods and inundation. Flood insurance is almost exclusively provided by the National Flood Insurance Program (NFIP) and is mandatory depending on the flood risk of the property insurers. Private insurers account only for a small but growing share of the market (Kousky, Kunreuther, Lingle, and Shabman, 2018). For a discussion of the NFIP, see Michel-Kerjan (2010) and Kunreuther (2018).

5. In April 2024, the average annual premium across U.S. states for $300,000 insurance coverage was $2,151, with the highest premiums in Florida ($5,770) and the lowest in Vermont ($799). For more information, see bankrate.com.

Homeowners insurers collected close to \$152 billion in premiums written in 2023, representing more than 15 percent of all direct premiums written by U.S. property and casualty (P&C) insurance companies (National Association of Insurance Commissioners, 2023b). As specified in the McCarran-Ferguson Act of 1945, insurance markets are subject to regulation by individual U.S. states. Insurance companies seeking to adjust prices, terms, and conditions, or application forms must submit a filing with the local regulatory authority in the affected U.S. state. In all states, most insurers take around one year to submit a new filing (see Appendix Figure 2.C.1). There are several reasons for this. First, homeowners insurance policies typically are one-year contracts. Hence, insurers must wait one year until the price change becomes effective in all contracts of the affected product. Second, insurers need to collect data on the performance of the affected product to justify new price changes. Third, state regulatory authorities also act as consumer protection agencies. Hence, insurance companies cannot arbitrarily often change prices.

Insurers must hold sufficient statutory capital to cover potential losses. The risk-based capital (RBC) ratio benchmarks an insurer's total equity to the regulatory required capital. If an insurer's RBC ratio is too low, the regulator requires the insurer to lay out a plan to enhance future capital or takes control of the insurer to protect policyholders. Insurers invest most of their assets in fixed-income securities and stocks to generate investment income, an essential determinant of insurance prices (Knox and Sørensen, 2024). Insurers' financial asset investments account for more than 70 percent of their total assets (see panel (a) of Appendix Figure 2.C.2). These investments generate income through interest and dividend payments, capital gains if marked to market, and realized gains upon sale if the asset had been accounted at historical cost. Stocks contribute to insurers' investment income mainly through capital gains as they are marked to market. Investment-grade bonds are held at historical cost and, therefore, mainly contribute through interest payments (see panel (b) of Appendix Figure 2.C.2). In contrast, high-yield bonds contribute through both as they are held at market values.

2.3 A Model of Insurance Prices and the Impact of Monetary Policy

To understand the impact of monetary policy on insurance prices, we consider a simple model of insurers subject to regulatory capital constraints in the spirit of Koijen and Yogo (2016). Our model features two periods, $t \in \{0, 1\}$, and a continuum of risk-neutral insurers $i \in [0, 1]$ subject to regulatory capital constraints. An exogenous risk-free rate determines the value of insurers' assets and liabilities and, thus, interacts with financial frictions.

2.3.1 Insurer Balance Sheets and Objective Function

Each insurer i is endowed with (interest-rate-sensitive) financial assets FA_i as well as preexisting liabilities L_i^0. Each insurer sets the price P_i to underwrite Q_i one-period contracts, where $Q_i = Q_i(P_i)$ is a downward-sloping demand function with constant elasticity ϵ.[6] The expected claims on all insurance contracts are normalized to 1 with present value $V = e^{-r_f}$, where r_f is the risk-free rate determined by the central bank. At $t = 0$, after selling insurance contracts, an insurer's total assets are, therefore, equal to the sum of the insurer's financial assets and the funds raised from insurance underwriting:

$$A_i \;=\; FA_i + P_i Q_i. \tag{2.3.2}$$

The insurer's total liabilities are:

$$L_i \;=\; L_i^0 + VQ_i. \tag{2.3.3}$$

As in Koijen and Yogo (2016), insurers face a regulatory cost of capital, where insurer i's statutory capital K_i at $t = 0$ is defined as:

$$K_i \;=\; A_i - (1+\rho)Q_i \;=\; FA_i + Q_i(P_i - (1+\rho)), \tag{2.3.4}$$

where $\rho \geq 0$ captures the capital requirement for insurance underwriting. Note that statutory capital is based on an insurer's expected future claims as opposed to the present value of these because P&C insurers are not allowed to discount their liabilities for regulatory purposes. The regulatory cost of capital is captured by the cost function

$$C_i \;=\; f\left(\frac{K_i}{L_i^0}\right), \tag{2.3.5}$$

which we assume to be downward-sloping, convex, continuous, and twice-differentiable.

Taken together, each insurer's objective is to set the price of insurance to maximize profits, Y_i, net of the regulatory capital cost:

$$\max_{P_i} Y_i - C_i, \tag{2.3.6}$$

where insurer i's profit is given by $Y_i = (P_i - V)Q_i$.

6. Following Knox and Sørensen (2024), we assume monopolistic competition among insurers, which results in all insurers facing downward-sloping demand for their insurance products with constant and identical demand elasticities:

$$\epsilon \;=\; -\frac{\partial \log Q_i}{\partial \log P_i}. \tag{2.3.1}$$

Insurers differ along two dimensions. First in the interest rate sensitivity of their financial assets, which is captured by the parameter

$$\alpha_i = \frac{\partial FA_i}{\partial r_f} < 0. \tag{2.3.7}$$

This parameter captures differences in the interest rate duration of investment portfolios and differences in the accounting of capital gains across asset classes. A lower (more negative) α_i corresponds to more sensitive financial assets. Second, insurers are born with varying amounts of preexisting liabilities, L_i^0, which, in the model, primarily implies varying levels of ex-ante regulatory constraints.

2.3.2 Insurance Prices and Their Sensitivity to Monetary Policy Shocks

Next, we consider how insurers optimally set insurance prices in equilibrium and how this decision is affected by changes in the risk-free interest rate r_f. First, we compute the optimal insurance price set by an insurer i.

Proposition 1. In equilibrium, the price of insurance set by insurer i is equal to

$$P_i = \left(1 - \frac{1}{\epsilon_i}\right)^{-1} \left(\frac{1 + \chi_i(1+\rho)}{1+\chi_i}\right) V, \tag{2.3.8}$$

where

$$\chi_i = -\frac{\partial C_i}{\partial K_i} > 0 \tag{2.3.9}$$

is insurer i's shadow cost of capital.

Proposition 1 shows that the equilibrium insurance price is the product of the markup that insurers can charge due to market power, $\left(1 - \frac{1}{\epsilon_i}\right)^{-1}$, the actuarial price, V, and the term $\frac{1+\chi_i(1+\rho)}{1+\chi_i}$, which captures the marginal effect of regulation on the cost of underwriting insurance contracts.[7]

In our model, we think of monetary policy as changes in the exogenous risk-free rate. Therefore, the effect of monetary policy on insurance prices is measured as the following comparative static.

Proposition 2. The effect of changes in the risk-free interest rate on insurer i's insurance price is:

$$\frac{\partial \log P_i}{\partial r_f} = -\frac{1 + \delta_i \alpha_i}{1 + \delta_i Q_i \epsilon_i V \left(e^{r_f}(1+\rho) - \frac{1+\chi_i(1+\rho)}{1+\chi_i}\right)}, \tag{2.3.10}$$

7. The pricing equation of Proposition 1 is identical to that of Koijen and Yogo (2016).

where

$$\delta_i \;=\; -\frac{\rho}{1+\chi_i(1+\rho)}\frac{\chi_i'}{1+\chi_i} \;\geq\; 0 \tag{2.3.11}$$

and $\chi_i' = \frac{\partial \chi_i}{\partial K_i}$.

The denominator of (2.3.10) is strictly positive, which implies that the effect of monetary policy on insurance prices is modulated by the relationship between α_i, which reflects asset sensitivity, and δ_i, which reflects the effect of financial frictions on monetary policy transmission to insurance prices. δ_i is an increasing function of both the regulatory capital charge, ρ, and the insurer's preexisting liabilities, L_i^0.[8] In the absence of financial frictions ($\rho = 0$) or ex-ante liabilities ($L_i^0 = 0$), the relative change in insurance prices moves one-to-one (negatively) with the risk-free rate, $\frac{\partial \log P_i}{\partial r_f} = -1$, as a higher risk-free rate implies a lower present value of future expected claims.

However, in the presence of financial frictions ($\rho > 0$) and liabilities ($L_i^0 > 0$), the effect of interest rate changes on insurance prices depends on the interest rate sensitivity of insurers' assets relative to that of the regulatory cost of capital. In particular, for a given interest sensitivity α_i, the insurance price sensitivity in Equation (2.3.10) is increasing in the amount of ex-ante liabilities, L_i^0. This effect is driven by the convexity of the cost function, C_i, which causes the depreciation of the insurer's financial assets to be more costly in terms of regulatory capital the more levered the insurer is (higher L_i^0). In contrast, the discounting of future expected claims is unaffected by the insurer's capital structure. Analogously, for a given amount of ex-ante liabilities L_i^0, the insurance price sensitivity in Equation (2.3.10) is increasing in the interest rate sensitivity of the insurer's financial assets. The reason is that monetary policy shocks tighten regulatory constraints more when the insurer's assets are more exposed to interest rate changes.

We can formalize these insights in the following conjectures.

Conjecture 1. In the presence of financial frictions, $\rho > 0$, and leverage, $L_i^0 > 0$, the effect of the risk-free interest on insurer *i*'s insurance price is increasing in the interest rate sensitivity of insurer *i*'s assets:

$$\frac{\partial}{\partial \alpha_i}\left\{\frac{\partial \log P_i}{\partial r_f}\right\} \;<\; 0. \tag{2.3.12}$$

8. To see this, note that if the regulatory capital charge ρ or the amount of preexisting liabilities L_i^0 approaches zero, then δ_i also approaches zero under the assumption that the first order derivative of the shadow cost of capital wrt. K_i, χ_i', approaches zero faster than the shadow cost of capital χ_i itself as L_i^0 approaches zero. This property holds for a wide variety of cost functions.

Conjecture 2. In the presence of financial frictions, $\rho > 0$, the effect of the risk-free interest on insurer i's insurance price is increasing in insurer's leverage:

$$\frac{\partial}{\partial L_i^0}\left\{\frac{\partial \log P_i}{\partial r_f}\right\} > 0. \tag{2.3.13}$$

Thus, whether a monetary policy shock increases or decreases insurance prices depends on the relationship between the insurer's assets' interest rate sensitivity and the insurer's regulatory cost of capital. If the insurer's assets are sufficiently interest rate sensitive relative to the regulatory cost of capital, a higher risk-free interest rate results in higher, not lower, insurance prices because the increase in capital costs dominates the discounting of future expected claims.

Conjecture 3. Insurance prices increase with higher risk-free interest rates if an insurer's assets are sufficiently interest rate sensitive and regulatory costs of capital sufficiently high:

$$\frac{\partial \log P_i}{\partial r_f} > 0 \Leftrightarrow \alpha_i < -\frac{1}{\delta_i}. \tag{2.3.14}$$

The intuition is that for an insurer with sufficiently interest-rate-sensitive assets, an increase in the risk-free rate causes the insurer's capital to become so expensive that the insurer increases insurance prices to underwrite fewer insurance contracts and relieve financial constraints. Note that this scenario is plausible in the context of P&C insurers because these write relatively short-term insurance contracts, implying limited discounting of expected claims, but hold long-duration assets with high interest rate sensitivity.

2.4 Data

In this section, we describe the data we use in our analysis. We construct three data sets to, first, analyze insurance prices, second, insurers' balance sheets, and third, housing and mortgage markets.

Insurance prices. U.S. insurance companies report all changes in the pricing of homeowners insurance products to state-level regulators. We obtain these rate filings submitted between 2009 and 2019 from S&P's Rate Watch database. We only consider rate changes approved by the state regulator (if approval is required).[9] From the rate filings, we obtain information on the effective change in the price of insurance (defined as the price change for the average \$1 of affected insurance

9. See Appendix Table 2.D.1 for a detailed listing of the cleaning steps.

premiums) as well as the insurer and state, the date of submission, and the effective date, the number of policyholders affected, and the amount of premiums written on affected products in the most recent year. Panel 1 of Table 2.4.1 describes the final sample comprising 26,975 rate filings submitted from 2009 to 2019. On average, insurers submit a rate filing once a year, increasing prices by 6 percent.

Insurers' balance sheets. We retrieve security-level data on insurers' end-of-year security holdings and all security transactions from their filings to the National Association of Insurance Commissioners (NAIC). The data contains extensive information about book and market values, security-specific cash flows (such as coupon payments), accrued interest, and amortization gains or losses for bonds held at book value. We use this data to decompose insurers' annual investment income according to underlying assets (stocks or fixed income) and revenue source (capital gains from holding the asset or realized gains from trading). We scale the investment income components with insurers' lagged total invested assets and take first differences to obtain the annual change in investment income.

We calculate two measures of insurers' portfolio sensitivity to interest rate changes. First, we calculate the average duration of insurers' fixed-income portfolios. We compute the end-of-year Macaulay duration of individual bond securities to do so. For this purpose, we use information on time to maturity, coupon rates and frequency from Mergent FISD. We compute bond yields based on corporate bond prices from TRACE Enhanced (cleaned following Dick-Nielsen, 2014), municipal bond prices from MSRB, and from the Federal Reserve for U.S. Treasuries.[10] Appendix 2.E gives a detailed description of our approach. We compute durations for most corporate bond, municipal bond, and U.S. Treasury investments, matching approximately 60 percent of the overall fixed-income portfolio and close to 40 percent of total assets (see Appendix Figure 2.E.1). We then aggregate security durations at the insurer level using the average duration weighted by book values. Second, we calculate the share of insurers' total assets that are mark-to-market. Broadly, the NAIC defines that insurers must mark-to-market stocks and high-yield bonds while investment-grade bonds and redeemable preferred stocks are held at historical cost. Applying these rules to insurers' end-of-year portfolio holdings, we define which securities are mark-to-market, aggregate the book values, and compute the end-of-year share of fair-value assets on insurers' balance sheets.

Panel 2 of Table 2.4.1 describes the final sample for the balance sheet analysis. On average, total annual investment income changes by 0.44 ppt, whereas changes in income from stocks are larger than changes in investment income from bonds.

10. The Federal Reserve publishes data on Treasury yield curves on federalreserve.org. The data is based on the approach in Gürkaynak, Sack, and Wright (2007) with minor modifications.

Home prices and mortgage data. We download data on county-level monthly home prices from Zillow.[11] In the main part of our analysis, we use the data on all home values, i.e., single-family residences and condos. We consider all county-month observations from 2010 to 2019. Moreover, we aggregate application-level data from the Home Mortgage Disclosure Act (HMDA) to a county-year level. Due to a break in the reporting of the HMDA data between 2017 and 2018, we consider all mortgage applications from 2010 to 2017. We calculate the number of mortgage applications and the associated mortgage amount in a county.

The average county in the sample experiences a monthly increase in home prices of 0.26 percent, equivalent to a 3.2 percent increase over a year (see Panel 3 of Table 2.4.1). On average, 3,990 mortgage applications in a year are reported in a county, amounting to $895 million, which implies that the average application amounted to a mortgage of almost $225,000.

Controls. We enrich our data with extensive insurer-level and state-level information. From insurers' quarterly regulatory filings to the NAIC, we access balance sheet and income statement information, including total assets, leverage, return on equity (ROE), risk-based capital (RBC) ratio, annualized underwriting gain (scaled by lagged assets), and investment income (scaled by lagged total invested assets). We use the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to calculate the 5-year trailing average and standard deviation of annual disaster damages (excluding floods) at the state level. Moreover, we obtain information on state-level annual personal income and GDP per capita from the Bureau of Economic Analysis (BEA), population numbers from the U.S. Census Bureau, and the annualized change in the state's house price index from the Federal Housing Finance Agency (FHFA).

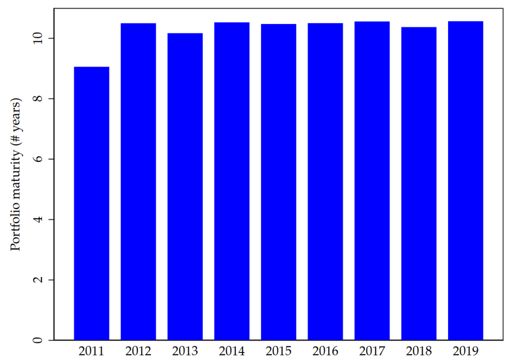
Finally, at the national level, we use the real GDP growth, CBOE Volatility Index (VIX), and national inflation measured by the Consumer Price Index, all obtained from FRED, to control for aggregate macroeconomic conditions. Table 2.D.2 in the Appendix provides detailed summary statistics for all control variables.

Monetary policy. To measure monetary policy surprises, we use the 10-year U.S. Treasury yield changes in a 30-minute window around FOMC meetings from Bauer and Swanson (2023). We use high-frequency changes in long-term rates for three reasons. First, high-frequency changes in market rates are widely used in the macroeconomic literature to elicit unanticipated shocks to monetary policy (Gürkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Swanson, 2021; Bauer and Swanson, 2023). Second, the average maturity of insurers' fixed income portfolio is approximately equal to ten years (see Figure 2.4.1). Therefore, fluctuations in long-term rates are relatively

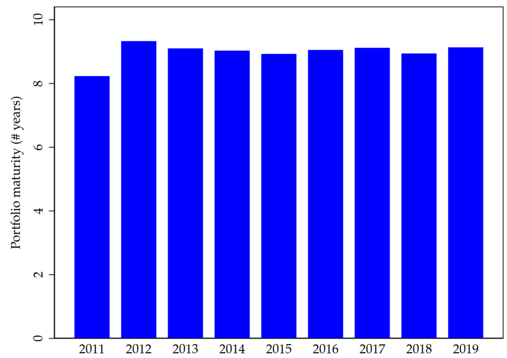
11. Source: zillow.com.

more important drivers for the market value of insurers' assets than fluctuations in short-term rates. Finally, in contrast to short-term rates, the zero lower bound did not constrain long-term rates during the time horizon of our sample. Thus, whereas the impact of monetary policy events on short-term rates was relatively muted during this period, the impact on long-term rates was highly significant and reflected unconventional monetary policy measures. The significant impact on long-term rates is consistent with prior literature (Hanson and Stein, 2015).

Figure 2.4.1. Maturity of insurers' fixed income portfolio



(a) Weighted by insurers' total assets



(b) Unweighted

Notes: This figure shows the average maturity of insurers' fixed-income portfolios over all insurance companies in our sample. Panel (a) shows the weighted average with insurers' total assets as weights; panel (b) shows the unweighted average. The data begins in 2011 because insurers have to report the maturity date of their fixed-income investments to the NAIC since 2011.

We also document the robustness of our results by using alternative measures for monetary policy shocks (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018), which are based on changes in short-term rates.[12]

12. For the the shocks of Gürkaynak, Sack, and Swanson (2005), we download the updated shock series from Acosta (2022), Miguel Acosta makes available on his webpage.

Table 2.4.1. Summary statistics

Panel 1: Filing analysis

	N	Mean	SD	1st	25th	Median	75th	99th
Filing information								
ΔPrice (%)	26,975	5.98	6.24	-7.20	0.60	5.00	9.50	26.80
Filing time	26,975	364.87	290.73	4.00	181.00	350.00	423.00	1,517.00
Insurer characteristics (insurer-quarter level)								
Assets (mn USD)	8,183	2,407.47	6,074.12	8.56	117.64	366.90	1,624.95	33,965.52
RBC ratio	8,183	11.98	15.05	3.13	5.98	8.49	12.46	121.57

Panel 2: Balance sheet analysis

	N	Mean	SD	1st	25th	Median	75th	99th
ΔInvestment income from								
Stocks (pp)	7,886	0.44	3.64	-9.96	-0.40	0.00	0.83	15.95
Bonds (pp)	7,886	-0.01	0.91	-3.10	-0.37	-0.05	0.30	3.38
Holding (pp)	7,886	0.36	3.76	-11.25	-0.55	0.00	0.91	15.78
Trading	7,886	0.08	1.45	-5.34	-0.30	0.00	0.39	5.83
Total (pp)	7,886	0.44	4.01	-10.42	-0.98	0.00	1.26	17.39
Portfolio sensitivity								
Duration	7,870	5.94	2.25	1.69	4.46	5.69	7.10	13.06
MTM share	7,886	12.77	15.44	0.00	0.29	7.74	19.80	70.05

Panel 3: Housing & mortgage markets analysis

	N	Mean	SD	1st	25th	Median	75th	99th
County-month analysis								
ΔHome value (%)	288,354	0.26	0.59	-1.31	-0.07	0.28	0.60	1.78
5-year damages (thd USD)	288,354	996.76	16,952.52	0.00	0.00	0.00	64.82	10,749.09
County-year analysis								
Mortgage applications	21,512	3,989.94	12,973.67	13.00	272.00	792.00	2,457.50	50,366.00
Amount (mn USD)	21,512	895.22	4,353.50	1.18	27.97	92.28	364.96	13,731.80

Panel 4: Monetary policy shocks

	N	Mean	SD	1st	25th	Median	75th	99th
6-month cumulative	132	-0.03	0.08	-0.35	-0.08	-0.01	0.04	0.09
End-of-year quarter	11	0.00	0.06	-0.15	-0.01	0.01	0.03	0.06

Table 2.4.1 continued.

Notes: This table shows the summary statistics for the main variables of the different samples used in the empirical analysis.

Filing information. *ΔPrice* is the effective change of the insurance price granted in the filing. *Filing time* is the number of days between the insurer's last and current filing in the same state.

Insurer characteristics. *Assets* is an insurer's total assets in a quarter. *RBC ratio* is an insurer's risk-based capital ratio at the end of a quarter.

Balance sheets. *ΔInvestment income* is the change in the insurer's annual investment income scaled by lagged total assets. *Duration* is the average duration of the insurer's end-of-year fixed-income portfolio. *MTM share* is the share of an insurer's total end-of-year assets that is marked-to-market.

Housing & mortgage markets analysis. *ΔHome value* is the county's monthly growth rate of home prices, including all types of homes. *5-yr damages* is the amount of natural disaster damages in USD in a county over the past 5 years. *Mortgage applications* is a county's yearly number of mortgage applications, i.e., originated mortgages, denied applications, and withdrawn applications. *Amount* is a county's yearly mortgage amount related to the submitted applications.

Monetary policy shocks. *6-month cumulative* is the sum of all high-frequency surprises in the 10-year U.S. Treasury yield around FOMC meetings over the past six months. *End-of-year quarter* is the sum of all high-frequency surprises in the 10-year U.S. Treasury yield around FOMC meetings over the last quarter of the year.

2.5 Monetary Policy and Insurance Prices

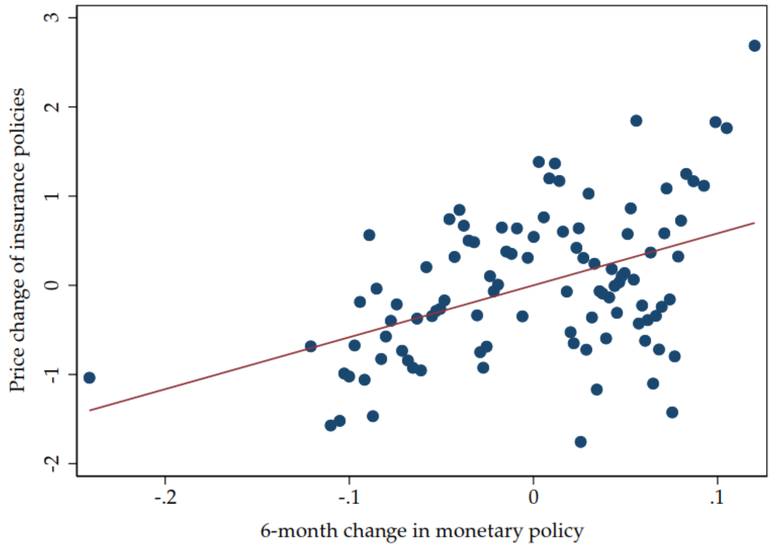
In this section, we document that contractionary monetary policy shocks are associated with a larger growth in insurance prices. Figure 2.5.1 depicts the relationship between insurance price changes and monetary policy surprises in the 10-year Treasury yield as a binned scatter plot. The two variables are clearly positively correlated: larger monetary policy surprises are associated with larger growth in insurance prices.

A critical identification concern is that monetary policy is endogenous to macroeconomic conditions that simultaneously affect insurance prices. Using monetary policy *surprises* instead of actual monetary policy decisions is the canonical methodology to address this concern. In the following, we provide additional evidence which supports a causal interpretation. For this purpose, we regress insurance price growth at the rate filing level on monetary policy surprises, controlling for aggregate and state-level macroeconomic conditions as well as insurer characteristics:

$$\Delta\text{Price}_f \;=\; \beta_{MP}\;\Delta\text{MP}_{(t-1:t-6)} + \gamma_I \boldsymbol{I} + \gamma_S \boldsymbol{S} + \gamma_M \boldsymbol{M} + u_{i,s} + v_{s,p} + \epsilon_f, \qquad (2.5.1)$$

where ΔPrice_f is the insurance price growth according to rate filing f by insurer i in state s in month t. The main coefficient of interest is β_{MP}, which measures the effect of monetary policy surprises on insurance price growth. $\Delta MP_{(t-1:t-6)}$ is the sum of high-frequency surprises in the 10-year Treasury yield for monetary policy events during the 6 months preceding filing f. We use aggregate monetary policy events over a relatively long time horizon because insurers infrequently change insurance prices, typically once a year (the results are robust to using the 1-year trailing sum of monetary policy events). Moreover, the longer time horizon ensures capturing the effect of transient rate changes rather than predictable reversals following monetary policy events (Hanson, Lucca, and Wright, 2021).

Figure 2.5.1. Monetary policy and insurance prices



Notes: This figure shows a binned scatter plot with the effective change in the insurance prices from insurers' filings on the y-axis and the sum of all monetary policy surprises measured as the changes in the 10-year U.S. Treasury yield in a 30-minute window around FOMC meetings over the preceding six months. The binned scatter plot includes insurer fixed effects.

$\boldsymbol{I}$, $\boldsymbol{S}$, and $\boldsymbol{M}$ are insurer-specific, state-specific, and aggregate controls, respectively. $\boldsymbol{I}$ includes insurers' *Log(Assets)*, *Leverage*, *ROE*, *RBC ratio*, *Underwriting gain*, and *Investment income*, all lagged by five quarters relative to filing f. These variables reflect insurers' financial characteristics and, in particular, profitability. State characteristics $\boldsymbol{S}$ include *Log(Mean 5-yr damage)*, *Log(SD 5-yr damage)*, *Log(Personal income per capita)*, *Log(GDP per capita)*, all lagged by one year relative to filing f, and ΔHPI, lagged by one quarter. Aggregate controls $\boldsymbol{M}$ include the 6-months trailing national GDP growth, ΔGDP, and CPI growth, ΔCPI, as well as the CBOE Volatility Index, *VIX*. These state-level and aggregate variables capture macroeconomic conditions that may affect monetary policy decisions and variation in disaster risk, a key component of homeowners insurance pricing. Finally, $u_{i,s}$ and $v_{s,p}$ are insurer-by-state and homeowners insurance product-by-state fixed effects, absorbing time-invariant differences across local insurance markets. We cluster standard errors at the insurer, the state, and the year-month level, accounting for potential auto-correlation of price growth and the fact that the main variation of interest is at the aggregate level.

Table 2.5.1 reports OLS estimates for Equation (2.5.1). In column (1), we include insurer-state and product-state fixed effects. The point estimate implies that an 8 bps monetary policy surprise (corresponding to its standard deviation) is associated with an approximately 0.5 ppt increase in insurance price growth, corresponding to 8% of its standard deviation. The effect is statistically significant at the 1% level. The magnitude and statistical significance are robust to including insurer, state, and aggregate control variables, as we show in columns (2) and (3). This suggests that the relationship between monetary policy and insurance prices is not driven by macroeconomic characteristics affecting both insurers and monetary policy decisions. Moreover, we document the robustness to using alternative measures of monetary policy surprises, namely those proposed by Nakamura and Steinsson (2018) and Gürkaynak, Sack, and Swanson (2005). In both cases, the coefficient on monetary surprises is positive and highly statistically significant (columns 4 and 5). Because these alternative measures rely on high-frequency surprises in *short-term* rates, we re-scale them by their respective coefficients in regressions with 10-year Treasury yield changes as the dependent variable. The re-scaled coefficients estimate the implied response of insurance price growth to shocks in the 10-year Treasury yield, similarly to the baseline coefficients. The magnitude of the re-scaled coefficients is comparable to that of the baseline coefficients, emphasizing the robustness of the result.

In Appendix Table 2.D.3, we show that our baseline result is robust to various alternative specifications. First, the positive effect of contractionary monetary policy surprises on insurance price growth is consistent across different sample periods. Second, it is robust to using alternative measures to control for inflation, such as PCE and state-level inflation, which we take from Hazell, Herreño, Nakamura, and Steinsson (2022). Third, the effect is robust to an alternative horizon used to aggregate monetary policy surprises. Specifically, we aggregate all monetary policy events since the previous rate filing in an alternative specification. Furthermore, we rule out that insurers adjust other variables in their rate filings, such as the number of policyholders affected, potentially dampening the impact via the extensive margin. In contrast, we find that the number of policyholders and amount of premiums affected by rate filings slightly *increase* after contractionary monetary policy surprises – although the effects are not statistically significant at the 5% level. We also document that actuarially justified price changes increase after contractionary monetary policy surprises, suggesting that insurers actively consider the impact of monetary policy on investment income.[13]

13. In rate filings, insurers calculate target prices that are necessary to meet future profitability goals. These target prices typically result from actuarial calculations based on the insurers' profits and losses, including their investment income.

Table 2.5.1. Monetary policy and insurance prices

	Dependent variable: $\Delta Price_f$				
	(1)	(2)	(3)	(4)	(5)
$\Delta \mathrm{MP}_{(t-1:t-6)}$	5.983***	4.122**	4.058**		
	[3.31]	[2.63]	[2.55]		
$\Delta \mathrm{NS}_{(t-1:t-6)}$				16.648***	
				[4.98]	
$\Delta \mathrm{Target}_{(t-1:t-6)}$					26.042***
					[5.36]
1 pp shift in 10-year US Treasury				4.076	5.019
Insurer Controls		Yes	Yes	Yes	Yes
State Controls			Yes	Yes	Yes
Macro Controls			Yes	Yes	Yes
Insurer-State FE	Yes	Yes	Yes	Yes	Yes
Product-State FE	Yes	Yes	Yes	Yes	Yes
No. of obs.	26,975	26,975	26,975	26,975	26,975
R^2	0.309	0.327	0.344	0.349	0.351
Within R^2	0.005	0.031	0.055	0.063	0.064

Notes: This table shows estimates for the relationship between monetary policy and changes in insurance prices, i.e., equation (2.5.1). The dependent variable $\Delta Price_f$ is the effective insurance price change of filing f. In columns (1) to (3), the independent variable, $\Delta \mathrm{MP}_{(t-1:t-6)}$, is the sum of all monetary policy surprises in the 10-year U.S. Treasury yield in the six months preceding the month the filing was submitted. In column (4), the independent variable $\Delta \mathrm{NS}_{(t-1:t-6)}$ is the sum of all monetary policy surprises identified by Nakamura and Steinsson (2018) in the six months preceding the month the filing was submitted. In column (5), the independent variable $\Delta \mathrm{Target}_{(t-1:t-6)}$ is the sum of all monetary policy surprises in the Fed Funds target rate from Gürkaynak, Sack, and Swanson (2005) in the six months preceding the month the filing was submitted. We control for several lagged insurer-level variables, i.e., *Log(Assets)*, *Leverage*, *RBC ratio*, *ROE*, *UW gain*, and *Investment income*, lagged state-level variables, i.e., *Log(Mean 5-yr damage)*, *Log(SD 5-yr damage)*, *Log(Income per capita)*, *Log(GDP per capita)*, and *ΔHPI*, and macroeconomic variables, i.e., *ΔGDP*, *VIX*, and *ΔCPI*. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. All continuous insurer-level variables are winsorized at the 1% and 99% levels. Standard errors are three-way clustered at the insurer, the state, and the year-month level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Finally, we address the concern that adjustments at the extensive margin of price changes may mitigate effects. Extending our sample to the insurer-by-state-by-year-month level, we start by estimating the following specification:

$$\begin{aligned}\mathbf{1}(\text{Rate filing}_{i,s,t}) \;=\; & \beta_{MP}\,|\Delta \mathrm{MP}_{(t-1:t-6)}| + \gamma_I \boldsymbol{I} + \gamma_S \boldsymbol{S} + \gamma_M \boldsymbol{M} \\ & + u_{i,s} + v_{s,season} + \epsilon_{i,s,t},\end{aligned} \tag{2.5.2}$$

where $\mathbf{1}(\text{Rate filing}_{i,s,t})$ is a dummy variable that equals one if insurer i files in state s in year-month t for a change of insurance prices. All other variables are defined as before. $u_{i,s}$ and $v_{s,season}$ are insurer-state and state-season fixed effects for state s and calendar month c, absorbing state-specific seasonality in filing behavior.

We use a three-way clustering of standard errors at the insurer, state, and year-month level. $|\Delta \text{MP}_{(t-1:t-6)}|$ is the absolute value of lagged cumulative monetary policy surprises. Thus, β_{MP} estimates whether insurers are likely to file for insurance price changes following monetary policy surprises with a larger magnitude (either contractionary or expansionary).

We find that the estimate for β_{MP} in Equation (2.5.2) is close to zero and insignificant (see Appendix Table 2.D.3), suggesting that monetary policy surprises do *not* affect the probability of price changes. The result is similar when we use an indicator for all product filings as the dependent variable, reflecting price changes and other changes in insurance supply, e.g., in the terms and conditions of products. This is consistent with the absence of an impact of monetary policy surprises on the propensity of insurers to change product characteristics. Finally, we construct a balanced panel of price changes at the monthly frequency for each insurer-state pair, including zeros in months without rate filings. The result is consistent with our baseline findings, emphasizing their robustness and the absence of extensive margin effects.[14]

2.6 Monetary Policy and Insurers' Investment Income

We argue that the impact of monetary policy surprises on insurance prices is modulated by their effect on insurers' asset investments. In the following, we document that contractionary monetary policy surprises depress insurers' investment income. The effect is stronger for investment income generated from stocks than for bonds and is driven by (1) the devaluation of mark-to-mark assets and (2) lower gains from trading bonds.

Insurers invest insurance premiums in financial assets to generate investment income, primarily stocks and bonds (including corporate bonds, municipal bonds, government bonds, and asset-backed securities). In aggregate, property insurers invest 80 percent of total assets in stocks and bonds (see panel (a) of Figure 2.C.2). On insurers' statutory balance sheet, these assets generate investment income through two mechanisms. First, holding securities generates income from interest and dividend payments, amortization (of assets held at book value), and market price fluctuations (of assets held at market value). Second, if insurers trade these securities, they realize gains or losses from either accrued interest (on asset

14. If an insurer submits two rate filings in the same state in the same month, we take the weighted average of $\Delta Price_f$ with the premiums written on the products as weights. It is important to note that the magnitude in the balanced panel is consistent with our baseline results. In the balanced panel, the point estimate for the coefficient on monetary policy surprises equals 0.341. Given that the average insurer submits a new rate filing every 12 months, this corresponds to a 4.092 ppt increase in insurance price growth *conditional* on a rate filing, which is close to the estimate in Table 2.5.1.

purchases) or the difference between market and book values at disposal (on asset sales).

Panel (b) of Figure 2.C.2 decomposes insurers' investment income in aggregate. The largest contributors to investment income are holdings of stocks and bonds, which, on average, account for approximately 30% and 50% of total investment income, respectively. Whereas stocks and high-yield bonds (with a credit rating below BBB) are held at market value, investment-grade bonds are held at book value. Therefore, the income from stock holdings tends to be more volatile than income from bond holdings.

We examine the impact of monetary policy on investment income in the following specification at the insurer-by-year level:

$$\Delta\text{Outcome}_{i,y} \;=\; \beta_{MP}\;\Delta\text{MP}_{Q4(y-1)} + \gamma_I \boldsymbol{I}_{i,y-1} + \gamma_M \boldsymbol{M}_y + u_i + \varepsilon_{i,y}, \tag{2.6.1}$$

where $\Delta\text{Outcome}_{i,y}$ is the change in insurer i's investment income component from year $y-1$ to year y. $\boldsymbol{I}_{i,y-1}$ and $\boldsymbol{M}_y$ are the same insurer controls and macroeconomic controls as in the previous section, respectively. u_i are insurer fixed effects. We use two-way clustered standard errors at the insurer and size quartile-year level. The main coefficient of interest is β_{MP}, which captures the impact of monetary policy surprises $\Delta\text{MP}_{Q4(y-1)}$, defined as the cumulative high-frequency changes in the 10-year U.S. Treasury yield around FOMC meetings in the fourth quarter of year $y-1$.

Table 2.6.1 shows the results of Equation (2.6.1) for different investment income components. Insurers' total investment income significantly declines following contractionary monetary policy surprises (column 1). The effect is economically sizable. We estimate that a 6 bps monetary policy surprise (its standard deviation in this sample) is followed by a decline in total investment income by 2.3 ppt, corresponding to 57% of its standard deviation. This effect is primarily driven by stock holdings (column 3). Investment income from stock holdings declines by 1.8 ppt in response to a 6 bps surprise, which explains 80% of the effect on total investment income. This finding is consistent with prior literature documenting the strong impact of monetary policy surprises on stock markets (Bernanke and Kuttner, 2005). Instead, we find that investment income from trading stocks does not significantly respond to monetary policy surprises (column 4). This finding is not surprising because stocks are already held at market value, and thus, gains and losses from trading essentially reflect bid-and-ask spreads.

Income from bond investments declines by 0.28 ppt in response to a 6 bps monetary policy surprise (column 5), corresponding to 30% of its standard deviation. Thus, bond investments contribute to 12% of the overall effect of monetary policy on total investment income. These are mainly driven by income from holding bonds (column 6) and, to a lesser extent, by realized income from trading bonds (column 7). Income from holding bonds results from amortization of investment-grade bonds, mark-to-market gains and losses of high-yield bonds, and investment-grade bonds with impaired credit quality, coupon payments, and redemption payments. Because coupon and amortization rates are fixed over a bond's lifetime, mark-to-market gains and losses account for the majority of the effect of monetary policy on income from holding bonds. Bonds not held at market value are revalued at market prices upon bond sales. The difference between book value and market value feeds into the investment income as a realized gain or loss, explaining the significant impact of monetary policy on realized income from trading bonds.

Table 2.6.1. Monetary policy and insurers' investment income

	Dependent variable: $\Delta Outcome_{i,y}$						
Asset:	Total	Stocks			Bonds		
Outcome:	Investment income	Investment income	From holding	From trading	Investment income	From holding	From trading
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta MP_{Q4(y-1)}$	-38.443***	-32.943***	-31.089***	-0.622	-4.661***	-3.243***	-1.146***
	[-18.20]	[-18.43]	[-17.64]	[-1.31]	[-7.51]	[-6.22]	[-3.58]
Insurer Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	7,886	7,886	7,886	7,886	7,886	7,886	7,886
R^2	0.304	0.288	0.242	0.063	0.112	0.188	0.051
Within R^2	0.283	0.265	0.223	0.034	0.083	0.145	0.026

Notes: This table shows estimates for the impact of monetary policy on insurers' investment income and its different components, i.e., equation (2.6.1). The dependent variable $\Delta Outcome_{i,y}$ is the change (in percentage points) in insurer i's investment income component scaled by lagged total assets from year $y-1$ to year y. In column (1), we consider total investment income, and in columns (2) to (7) consider the different components of insurers' investment income from their stock holdings and trades, columns (2) to (4), and bond holdings and trades, columns (5) to (7). The independent variable, $\Delta MP_{Q4(y-1)}$, is the sum of all monetary policy surprises in the 10-year U.S. Treasury yield in the fourth quarter of year $y-1$. We control for several lagged insurer-level variables, i.e., *Log(Assets)*, *Leverage*, *RBC ratio*, *ROE*, *UW gain*, and *Investment income*, and *ΔHPI*, and macroeconomic variables, i.e., *ΔGDP*, *VIX*, and *ΔCPI*. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. All continuous insurer-level variables are winsorized at the 1% and 99% levels. Standard errors are two-way clustered at the insurer and the size quartile-year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

In the following, we provide further evidence that monetary policy surprises affect insurers' investment income through their impact on asset prices. First, we hypothesize that the response in the income from holding bonds should be stronger for insurers with a more interest-rate-sensitive bond portfolio, which is reflected in its duration. Bonds with a longer duration experience larger price declines in response to higher interest rates. Based on our duration measure, we define by $High\ duration_{i,y-1}$ an indicator variable for insurer i's portfolio duration being in the top quintile of the annual cross-sectional distribution. Such insurers see particularly strong declines in bond prices following contractionary monetary policy surprises (see Appendix Table 2.E.1).

Table 2.6.2. Determinants of monetary policy's impact on insurers' investment income

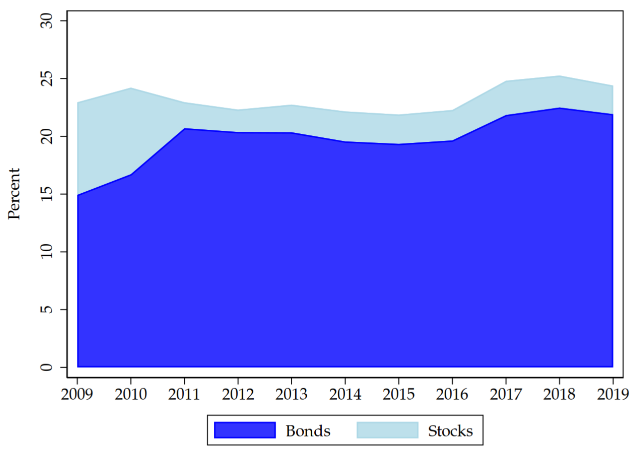
	Dependent variable: $\Delta Outcome_{i,y}$					
Asset:	Stocks	Bonds		Stocks	Bonds	
Outcome:	Unrealized gains	Unrealized gains	Realized gains	Unrealized gains	Unrealized gains	Realized gains
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta MP_{Q4(y-1)}$	-30.146***	-1.014***	-1.128***	-32.280***	-1.300***	-1.059***
	[-16.02]	[-6.24]	[-3.14]	[-17.22]	[-6.81]	[-3.09]
High $duration_{i,y-1}$	-0.110	-0.002	-0.040			
	[-0.63]	[-0.19]	[-0.98]			
High $duration_{i,y-1}$ $\times$ $\Delta MP_{Q4(y-1)}$	1.652	-0.898***	-0.038			
	[0.71]	[-3.87]	[-0.07]			
Low $CF_{i,y-1}$				0.169	0.010	0.012
				[1.36]	[0.85]	[0.37]
Low $CF_{i,y-1}$ $\times$ $\Delta MP_{Q4(y-1)}$				4.614**	0.362	-1.306**
				[2.20]	[1.45]	[-2.58]
Insurer Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	7,869	7,869	7,869	6,293	6,293	6,293
R^2	0.236	0.065	0.051	0.264	0.067	0.056
Within R^2	0.218	0.051	0.026	0.245	0.051	0.029

Notes: This table estimates the heterogeneous impact of monetary policy on insurers' investment income across liquidity shocks and fixed-income portfolio duration. We estimate regression equation (2.6.1) with an interaction term with the variables *Low* $CF_{i,y-1}$ and *High* $duration_{i,y-1}$. The dependent variable $\Delta Outcome_{i,y}$ is the change in percentage points in insurer i's investment income component scaled by lagged total invested assets from year $y-1$ to year y. The main independent variable, $\Delta MP_{Q4(y-1)}$, is the sum of all monetary policy shocks in the fourth quarter of year $y-1$. *High* $duration_{i,y-1}$ is an indicator variable that takes the value 1 if insurer i's fixed income portfolio duration in year $y-1$ is in the fifth quintile of the annual cross-sectional distribution of this variable. *Low* $CF_{i,y-1}$ is an indicator variable that takes the value 1 if the insurer i's cash flow from underwriting in year $y-1$ scaled by lagged cash holdings is in the fifth quintile of the pooled distribution of this variable. We control for several lagged insurer-level variables, i.e., *Log(Assets)*, *Leverage*, *RBC ratio*, *ROE*, *UW gain*, and *Investment income*, and macroeconomic variables, i.e., *ΔGDP*, *VIX*, and *ΔCPI*. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. All continuous insurer-level variables are winsorized at the 1% and 99% levels. Standard errors are two-way clustered at the insurer, and the size quartile-year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

In Table 2.6.2, we estimate Equation (2.6.1) with an interaction term between monetary policy surprises and *High* $duration_{iy-1}$. Duration significantly affects the pass-through of monetary policy surprises to investment income. Insurers with a long bond portfolio duration experience an almost twice as large response of their income from holding bonds (column 2). This finding is consistent with a longer duration, implying larger market value losses in response to rate hikes. The differential effect of a longer duration is muted for income from trading bonds (column 3), suggesting that insurers selectively trade bonds to avoid realizing losses (consistent with the results by Ellul, Jotikasthira, Lundblad, and Wang, 2015). A possible concern is that our measure for duration picks up insurer characteristics other than their bond portfolio's interest rate sensitivity. To address this concern, we conduct a placebo test using income from stock holdings as a dependent variable. We expect that the pass-through of monetary policy to stock investments does *not* significantly depend on bond portfolio duration. Column (1) is consistent with this expectation, as the coefficient on the interaction term is close to zero and not significantly different from zero.

Second, we focus on the significant response of realized income from trading bonds. As contractionary monetary policy surprises reduce bond prices, insurers may avoid realizing losses by not selling bonds.[15] Although insurers, on average, sell a significant part of their assets (see Figure 2.6.1), there is significant variation across insurers. In particular, insurers may have to realize losses when faced with significant liquidity needs (Ge and Weisbach, 2021; Liu, Rossi, and Yun, 2021; Massa and Zhang, 2021). Therefore, we expect insurers with higher liquidity need to experience a stronger decrease in their realized bond investment income.

Figure 2.6.1. Asset sales by insurers



Notes: This figure shows the share of total invested assets split by bonds and stocks that insurers sell in a year over the sample period. Bonds encompass all fixed-income securities, i.e., mainly corporate bonds, municipal bonds, U.S. Treasuries, and asset-backed securities.

To test this hypothesis, we measure insurers' liquidity needs as the ratio of the negative operating cash flow (losses paid less premiums collected) scaled relative

15. Ellul, Jotikasthira, Lundblad, and Wang (2015) document that insurers actively adjust their trading behavior to avoid realizing losses.

to lagged cash holdings. We then indicate with the variable $Low\ CF_{i,y-1}$ the 20% insurers with the largest liquidity need in the pooled distribution. This threshold corresponds to a liquidity need of approximately 20 percent of lagged cash holdings and, thus, indicates the depletion of a substantial share of insurer liquidity (see panel (b) of Figure 2.C.3).

Consistent with the hypothesis, we find that liquidity-constrained insurers experience a significantly larger drop in their investment income from bond trading in response to contractionary monetary policy surprises (column 6). Instead, we do not find a similar effect for the investment income from holding stocks or the investment income from holding bonds (columns 4 and 5), consistent with these being driven by the impact of monetary policy on asset prices rather than liquidity needs. In robustness analyses, we provide further evidence of the investment income response from bond trades at a higher frequency, exploiting granular data on bond transactions. More specifically, we calculate the weekly change in insurers' realized gains and losses in the weeks around monetary policy events. The results are consistent with the baseline findings, emphasizing their robustness (see Appendix Table 2.D.4).

2.7 Monetary Policy and Insurance Prices in the Cross-Section of Insurers

The model in Section 2.3 predicts that contractionary monetary policy shocks increase insurance prices because they dampen insurers' investment income, which tightens regulatory constraints. This effect strengthens with (a) the severity of regulatory frictions and (b) the investment income response to monetary policy. In the following, we provide empirical evidence for these predictions.

First, we examine the role of insurers' regulatory capital constraints. The regulatory capital (RBC) ratio is defined as an insurer's level of regulatory capital relative to regulatory required capital. We document that investment income is an important determinant of regulatory capital. In regressions of annual changes in regulatory capital on investment income, we estimate that a $1 higher investment income translates into 46 cents larger regulatory capital, as reported in column (1) of Table 2.7.1.[16] After controlling for time-invariant heterogeneity across insurers and aggregate shocks, using insurer and year fixed effects, the coefficient implies a one-to-one pass-through of investment income to regulatory capital (column 2). We also assess the relative importance of different investment income components. Mark-to-market gains and losses from holding stocks and bonds exhibit the largest

16. In unreported regressions, we verify that this relationship is robust to scaling both variables with lagged regulatory capital.

pass-through to regulatory capital, highlighting their importance as determinants of regulatory constraints.

Table 2.7.1. Insurers' investment income and changes in regulatory capital

	Dependent variable: $\Delta Regulatory\ capital_{i,y}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Investment income (in USD)$_{i,y}$	0.464***	0.966***				
	[3.34]	[11.94]				
From stocks			0.781***	1.013***		
			[5.78]	[13.15]		
From bonds			-0.010	0.757***		
			[-0.08]	[5.15]		
From holding stocks					0.858***	0.998***
					[7.51]	[10.36]
From trading stocks					-0.084	0.316*
					[-0.30]	[1.78]
From holding bonds					0.088	0.850***
					[0.62]	[9.34]
From trading bonds					-0.164	0.375
					[-0.17]	[0.47]
Insurer FE		Yes		Yes		Yes
Year FE		Yes		Yes		Yes
No. of obs.	6,994	6,968	6,994	6,968	6,994	6,968
R^2	0.229	0.561	0.285	0.562	0.387	0.608
Within R^2	0.229	0.308	0.285	0.310	0.387	0.382

Notes: This table shows estimates for the impact of investment income collected from insurers' security investments on the change in insurers' regulatory capital, i.e., we estimate:

$$\Delta\text{Regulatory capital}_{i,y} = \alpha + \beta\ \text{Investment income}_{i,y} + \varepsilon_{i,y}.$$

The dependent variable *ΔRegulatory capital*$_{i,y}$ is the change in insurer i's regulatory capital in USD from year $y-1$ to year y. The independent variable *Investment income*$_{i,y}$ is the investment income of insurer i generated in year y in USD. In columns (3) to (6), we split insurers' investment income into the different components. Standard errors are two-way clustered at the insurer, and the size quartile-year level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Second, we explore the role of regulatory frictions in the baseline regression (2.5.1) of insurance price changes on monetary policy surprises. For this purpose, we sort insurers according to their lagged capital ratios. To take potential heterogeneity in insurers' benchmark capital ratio into account (capital ratios are widely dispersed across insurers), we focus on deviations from an insurer's trailing average regulatory capital (RBC) ratio:

$$\text{RBC gap}_{i,y-1} = \overline{\text{RBC}}_{i,(y-7):(y-2)} - \text{RBC}_{i,y-1} = \frac{1}{6}\sum_{\tau=2}^{7}\text{RBC}_{i,y-\tau} - \text{RBC}_{i,y-1}. \quad (2.7.1)$$

The larger *RBC gap*$_{i,y-1}$, the lower the capital ratio in year $y-1$ relative to its trailing average. Thus, it is a measure of insurer i's regulatory constraints. Motivated by our model's predictions, we expect insurers with a higher *RBC gap* to increase prices more after contractionary monetary policy surprises. To formally test this prediction, we interact monetary policy surprises with indicator variables for the terciles of *RBC gap*$_{i,y-1}$ in Equation (2.5.1):

$$\begin{aligned} \Delta\text{Price}_f = \; & \beta_C \text{ Constrained}_{i,y-1} \times \Delta\text{MP}_{(t-1:t-6)} \\ & + \beta_I \text{ Intermediate}_{i,y-1} \times \Delta\text{MP}_{(t-1:t-6)} + \beta_{MP}\; \Delta\text{MP}_{(t-1:t-6)} \\ & + \gamma_I \boldsymbol{I} + \gamma_S \boldsymbol{S} + \gamma_M \boldsymbol{M} + u_{i,s} + v_{s,p} + \epsilon_f, \end{aligned} \quad (2.7.2)$$

where ΔPrice_f is the insurance price growth in rate filing f submitted at time t (in months) in year y. *Constrained*$_{i,y-1}$ and *Intermediate*$_{i,y-1}$ are indicator variables that take the value 1 if insurer i's *RBC gap* is in the third and second tercile of the pooled distribution, respectively. All other variables are defined as before. β_C and β_I estimate the differential impact of monetary policy surprises on highly and intermediately constrained insurers relative to unconstrained insurers.

Table 2.7.2 reports the estimated coefficients. We find that monetary policy surprises primarily affect regulatory-constrained insurers. The coefficient β_{MP} on the baseline term is not significantly different from zero, suggesting that unconstrained insurers do not increase prices in response to contractionary monetary policy surprises (column 1). The coefficient β_I on the interaction term with intermediately constrained insurers is also not significantly different from zero. Thus, there is no significant difference between unconstrained and intermediately constrained insurers. In contrast, the coefficient β_C on the interaction term with constrained insurers is positive and significant. The magnitude of this coefficient is close to that in our baseline results (in Table 2.5.1), suggesting that constrained insurers primarily drive the average effect of monetary policy surprises.

Because the coefficients β_C and β_I on the interaction terms rely on the *differential* impact of monetary policy across insurers, we can include state-by-time fixed effects (column 2) as well as state-by-time-by-product fixed effects (column 3). These absorb aggregate variation (including monetary policy) at the state and the state-by-product level, respectively. This alleviates the concern that the results may be driven by unobserved shocks that simultaneously affect prices and regulatory constraints. The coefficients remain similar in magnitude, with that on constrained insurers being significantly positive at the 1% level. These results highlight the importance of regulatory frictions for the transmission of monetary policy to insurance prices.

Table 2.7.2. Determinants of insurance prices

	Dependent variable: $\Delta Price_f$				
Constraints:	Regulatory capital			+High duration	+High MTM share
	(1)	(2)	(3)	(4)	(5)
$\Delta MP_{(t-1:t-6)}$	2.326 [1.10]				
$Intermediate_{i,y-1} \times \Delta MP_{(t-1:t-6)}$	-0.236 [-0.11]	0.605 [0.27]	0.210 [0.10]	-1.692 [-0.79]	-0.153 [-0.06]
$Constrained_{i,y-1} \times \Delta MP_{(t-1:t-6)}$	5.686** [2.39]	6.566*** [3.24]	5.584*** [3.34]	0.857 [0.69]	3.373** [2.10]
High $sensitivity_{i,y-1} \times \Delta MP_{(t-1:t-6)}$				-1.748 [-0.72]	-3.475 [-1.28]
High $sensitivity_{i,y-1} \times Intermediate_{i,y-1}$				-0.368 [-0.94]	0.066 [0.19]
High $sensitivity_{i,y-1} \times Constrained_{i,y-1}$				-0.048 [-0.13]	-0.811** [-2.34]
High $sensitivity_{i,y-1} \times Int'ediate_{i,y-1} \times \Delta MP_{(t-1:t-6)}$				6.203 [1.49]	1.897 [0.42]
High $sensitivity_{i,y-1} \times Constr'ed_{i,y-1} \times \Delta MP_{(t-1:t-6)}$				12.599*** [3.19]	13.049** [2.35]
Other interaction terms	Yes	Yes	Yes	Yes	Yes
Insurer Controls	Yes	Yes	Yes	Yes	Yes
State Controls	Yes				
Macro Controls	Yes				
Insurer-State FE	Yes	Yes	Yes	Yes	Yes
Product FE		Yes			
Product-State FE	Yes				
State-Year-Month FE		Yes			
Product-State-Year-Month FE			Yes	Yes	Yes
No. of obs.	26,975	26,049	23,024	22,904	23,024
R^2	0.345	0.577	0.676	0.678	0.677
Within R^2	0.056	0.014	0.014	0.016	0.015

Notes: This table shows estimates for the relationship between monetary policy and changes in insurance prices across regulatory and portfolio constraints. The dependent variable $\Delta Price_f$ is the effective insurance price change of filing f. The main independent variable, $\Delta MP_{(t-1:t-6)}$, is the sum of all monetary policy surprises in the 10-year U.S. Treasury yield in the six months preceding the month the filing was submitted. $Constrained_{i,y-1}$ ($Intermediate_{i,y-1}$) is an indicator variable that takes the value of 1 if insurer i's RBC ratio gap at the end of year $y-1$, i.e., the average of its RBC ratio over the previous six years minus its RBC ratio, is in the third (second) tercile of the pooled distribution of this variable. *High* $sensitivity_{i,y-1}$ is an indicator variable that takes the value of 1 if insurer i's portfolio is highly sensitive to monetary policy. We define *High sensitivity* using two approaches. In column (4), insurer i's portfolio is highly sensitive if insurer i's average fixed income portfolio duration is in the third tercile of the annual cross-sectional distribution of this variable at the end of year $y(f)-1$. In column (5), insurer i's portfolio is highly sensitive if insurer i's share of assets mark-to-market at the end of year $y(f)-1$ is in the fifth quintile of the pooled distribution. We control for several lagged insurer-level variables, i.e., *Log(Assets)*, *Leverage*, *RBC ratio*, *ROE*, *UW gain*, and *Investment income*, lagged state-level variables, i.e., *Log(Mean 5-yr damage)*, *Log(SD 5-yr damage)*, *Log(Income per capita)*, *Log(GDP per capita)*, and *ΔHPI*, and macroeconomic variables, i.e., *ΔGDP*, *VIX*, and *ΔCPI*. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. All continuous insurer-level variables are winsorized at the 1% and 99% levels. Standard errors are three-way clustered at the insurer, the state, and the year-month level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Finally, we consider how regulatory frictions interact with the pass-through of monetary policy to insurers' investment income. Our model predicts that a larger sensitivity of investment income to monetary policy amplifies its impact on prices for regulatory-constrained insurers. To test this prediction, we interact the regulatory constraints indicators with two measures of portfolio sensitivity. The first measure is the interest rate duration of insurers' bond portfolio, which reflects the pass-through of monetary policy to asset prices (see Section 2.6). We define an indicator variable that takes the value 1 if an insurer's portfolio duration in the year before filing f is in the third tercile of the annual cross-sectional distribution.

In column (4), we include triple interaction terms of monetary policy surprises, regulatory constraints, and portfolio duration. We use granular fixed effects at the product-by-state-by-time level to absorb any potentially confounding state-specific shocks to insurance product markets, exploiting cross-sectional variation within states to identify the coefficients. The coefficient on the triple interaction term for constrained insurers is significantly different from zero at the 1% level and positive, whereas all other interaction terms are not statistically different from zero (yet, with a sizable and positive coefficient on the triple interaction term with intermediately constrained insurers). Thus, regulatory-constrained insurers with a longer bond portfolio duration respond significantly more to monetary policy surprises compared to less constrained insurers.

The second measure of portfolio sensitivity is the share of insurers' assets held at market value, which corresponds to the share of stock and high-yield bond investments. This measure is motivated by the strong impact of monetary policy surprises on the investment income from market value changes of these assets, documented in Section 2.6. We define an indicator variable that takes the value 1 if an insurer's share of mark-to-market assets (MTM share) in the year before filing f is in the fifth quintile of its pooled distribution.

In column (5), we include triple interaction terms of monetary policy surprises, regulatory constraints, and MTM share. As before, we include granular fixed effects at the product-by-state-by-time level. The coefficient on the triple interaction term for constrained insurers significantly differs from zero at the 5% level and is positive. Thus, regulatory-constrained insurers with a larger MTM share respond significantly more to monetary policy surprises than less constrained insurers.

These results are consistent with our model's predictions. They suggest that monetary policy surprises are transmitted to insurance markets through their effect on asset prices, amplified by regulatory frictions.

2.8 Effects on Housing Markets

This section presents evidence that insurers' response to monetary policy transmits to housing markets. We construct a measure of monetary policy exposure of *local* insurance markets and document that residential real estate markets in areas with more exposed insurers are more responsive to monetary policy.

As we document in Section 2.2, homeowners insurance accounts for a substantial share of housing costs. Therefore, changes in insurance supply may have significant effects on home purchase decisions. The marginal buyer's willingness to pay may be lower in response to higher insurance prices, especially in areas with high disaster risk. In such areas, buyers face a substantially higher risk of property damage, while insurance payments account for a particularly large share of housing costs.

To examine the transmission to home prices, we estimate local projections (Jordà, 2005) of home prices, i.e.,

$$\begin{aligned} P_{c,t+h} - P_{c,t-7} \; = \; & \beta_I^h \; \phi_{s,t} \times \Delta\mathrm{MP}_{(t-1:t-6)} + \beta_{MP}^h \; \Delta\mathrm{MP}_{(t-1:t-6)} \\ & + \boldsymbol{\gamma}^h \boldsymbol{X} + u_{c,season} + \varepsilon_{c,t+h}. \end{aligned} \tag{2.8.1}$$

$P_{c,t+h}$ and $P_{c,t-7}$ are the natural logarithm of the average home price in county c in month $t+h$ and $t-7$, respectively. $\Delta MP_{(t-1:t-6)}$ is the sum of high-frequency surprises in the 10-year Treasury yield for monetary policy events during the lagged 6 months. $\boldsymbol{X}$ is a vector of county-level controls, which include the county's population density, annual growth in personal income per capita, GDP, and population, and macroeconomic controls, i.e., the VIX, GDP growth, and CPI inflation over the past six months. Moreover, following standard practice in local projections, we control for lags of monthly price changes in county c. $u_{c,season}$ denotes county-by-calendar month fixed effects, which absorb seasonality in home prices throughout the calendar year.

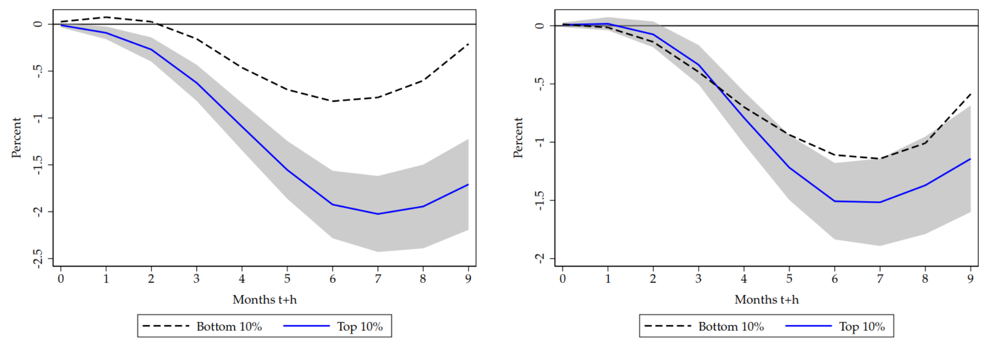
The key explanatory variable is $\phi_{s,t}$, which measures the exposure of insurers in state s (where county c is located) to monetary policy. We compute $\phi_{s,t}$ based on columns (4) and (5) in Table 2.7.2. Specifically, for each specification, we define by $\widehat{\Delta\mathrm{Price}_f}(\Delta\mathrm{MP})$ the predicted price growth in filing f as a (linear) function of monetary policy surprises. Then, $\hat{\phi}_f = \widehat{\Delta\mathrm{Price}_f}(1) - \widehat{\Delta\mathrm{Price}_f}(0)$ is the filing-specific slope of price growth with respect to monetary policy surprises. Finally, $\phi_{s,t}$ is the average of $\hat{\phi}_f$ at the state-by-month level weighted by the amount of (lagged) premiums affected by rate filing f.[17] As the previous results show, a larger value of $\phi_{s,t}$ indicates that insurers in state s increase prices to a larger extent in response to contractionary monetary policy surprises. We distinguish between monetary policy exposure $\phi_{s,t}$ based on either bond portfolio duration or MTM share.

Figure 2.8.1 shows the results of local projection estimations for duration-based exposure in panel (a) and for MTM-based exposure in panel (b). The black dashed line plots the effect of monetary policy on home prices for counties with

17. We exploit that monetary policy does not affect the extensive margin of rate filings (see Appendix Table 2.D.3).

less-exposed insurers (defined as those in the 10th percentile of $\phi_{s,t}$), whereas the blue solid line plots that for exposed insurers (defined as those in the 90th percentile). Both exposed and unexposed counties experience declining home prices in response to contractionary monetary policy surprises, consistent with prior results in the literature (Gorea, Kryvtsov, and Kudlyak, 2023). However, the effect is significantly stronger in counties that experience a stronger decline in insurance supply, indicated by larger insurer exposure $\phi_{s,t}$. The differential effect is economically significant. Considering the results from panel (a) of Figure 2.8.1, a 1 percentage point increase in the 10-year U.S. Treasury yield reduces home prices over the following six months by about 0.3% in counties with a low insurer sensitivity but by more than 1% in counties with a high insurer sensitivity. The result is similar in statistical and economic significance when using the MTM-based exposure measure, emphasizing its robustness. Moreover, in Appendix Figures 2.C.4 and 2.C.5, we show that the results are robust to using more granular home price indices, i.e., for single-family homes, condos, and different terciles of the home value distribution.

Figure 2.8.1. Home prices, insurers' sensitivity, and monetary policy



(a) Duration ϕ **(b)** MTM share ϕ

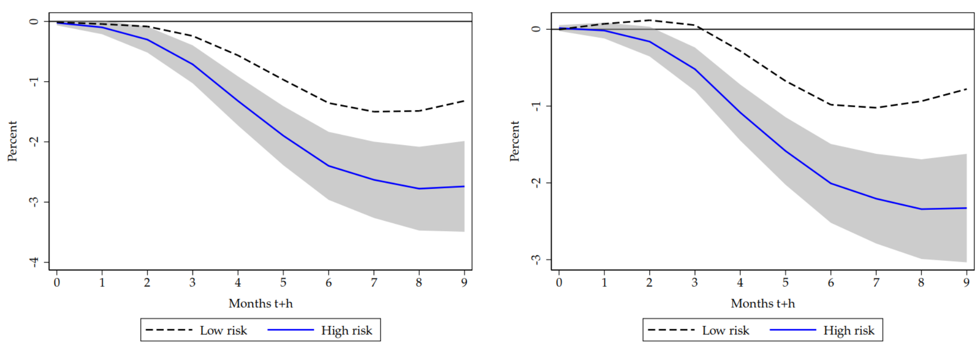
Notes: This figure shows the local projection of monetary policy's effect on home prices and the interaction with insurers' sensitivity. The black dashed line represents the effect of a 1 percentage point surprise in the 10-year U.S. Treasury yield over the previous six months on home prices at the 10th percentile of the pooled distribution of insurers' sensitivity. The blue solid line represents the effect at the 90th percentile of the pooled distribution of insurers' sensitivity. The gray area plots the corresponding 95% confidence intervals. Panel (a) shows the effect of monetary policy on home prices using the duration-based measure of insurers' sensitivity. Panel (b) shows the effect of monetary policy on home prices using the mark-to-market assets-based measure of insurers' sensitivity.

The findings suggest that insurers amplify monetary policy transmission to home prices. We expect that this effect strengthens when insurance premiums account for a larger share of housing costs. A primary determinant of insurance premiums is exposure to natural disasters (Keys and Mulder, 2024). Because it seems unlikely that real estate demand or supply in counties with a larger disaster exposure respond differently to monetary policy, exploiting variation in disaster exposure is also helpful to alleviate the concern that insurer exposure $\phi_{s,t}$ may be correlated with potential confounders at the state level.

We define an indicator variable *High risk*$_{c,t}$, which takes the value of 1 if county c experienced natural disaster damages over the lagged 5 years. There is substantial variation in *High risk*$_{c,t}$ both in the cross-section of counties and for a given county over time (see Appendix Figure 2.C.6). Some counties rarely experience disaster damage, while other counties are at high risk, especially those in coastal areas. We amend Equation (2.8.1) by including a triple interaction term of *High risk*$_{c,t}$ with insurer exposure $\phi_{s,t}$ and monetary policy surprises.

Figure 2.8.2 plots the effect of monetary policy surprises on home prices in exposed states (within the 90th percentile of $\phi_{s,t}$) for high-risk counties (solid blue line)and low-risk counties (dashed black line). The figure shows that home prices in high-risk counties respond significantly more to monetary policy surprises. Again, the findings are robust across definitions of the exposure measure $\phi_{s,t}$.

Figure 2.8.2. Disaster exposure and monetary policy transmission



(a) Duration ϕ

(b) MTM share ϕ

Notes: This figure shows the local projection of the interaction of monetary policy and insurers' sensitivity for high-risk and low-risk counties. The black dashed line represents the effect of a 1 percentage point surprise in the 10-year U.S. Treasury yield over the previous six months on home prices at the 90th percentile of the pooled distribution of insurers' sensitivity for counties with low risk, i.e., counties that have not experienced disaster damages in the prior 5 years. The blue solid line represents the effect at the 90th percentile of the pooled distribution of insurers' sensitivity for counties with high risk, i.e., counties that have experienced disaster damages in the prior 5 years. The gray area plots the corresponding 95% confidence intervals. Panel (a) uses the duration-based measure of insurers' sensitivity to monetary policy. Panel (b) uses the mark-to-market assets-based measure of insurers' sensitivity to monetary policy.

In the Appendix, we provide further evidence on the insurance channel, exploiting heterogeneity in local insurance regulators' approval time. More specifically, we estimate Equation (2.8.1) separately for states with fast and slow insurance regulators. We find that the negative impact on home prices materializes faster in states where regulators are faster, whereas slow states eventually catch up.[18] Because regulators' approval time is unlikely to correlate with unobserved confounders in the real estate market, this result further highlights the robustness of the baseline findings.

Finally, we show that, by reducing real estate demand, the monetary policy transmission through insurance markets also affects the banking sector. For this purpose, we examine local mortgage markets. We estimate the effect of insurers' monetary policy exposure on county-level mortgage applications in the following regression:

$$\begin{aligned} \Delta\text{Log(Mortgage applications)}_{c,y} \;=\; & \beta_I \; \phi_{s,y} \times \Delta\text{MP}_{Q4(y-1)} \\ & + \beta_{MP} \; \Delta\text{MP}_{Q4(y-1)} + \boldsymbol{\gamma X} + u_c + \varepsilon_{c,y} \end{aligned} \tag{2.8.2}$$

where *Log(Mortgage Applications)*$_{c,y}$ is the natural logarithm of the number of mortgage applications submitted in county c in state s in year y, a common measure for mortgage demand. These include all originated loans, withdrawn applications, and denied applications. As before, $\Delta\text{MP}_{Q4(y-1)}$ is the sum of high-frequency changes in the 10-year U.S. Treasury yield around FOMC meetings in the fourth quarter of year $y-1$. $\boldsymbol{X}$ is the vector of control variables we used above. We include $\Delta\text{Log(Mortgage applications)}_{c,y-1}$ as a control variable to account for persistence.

$\phi_{s,y}$ is insurers' exposure to monetary policy in state s in which county c is located measured in the first month of year y. Table 2.8.1 reports the estimated coefficients using the duration-based $\phi_{s,y}$. In column (1), we report the baseline effect of monetary policy on the change in mortgage applications. We find that contractionary monetary policy surprises are followed by a lower mortgage demand. In column (2), we interact monetary policy with insurer exposure. The coefficient on this interaction term is negative but not precisely estimated. In column (3), we include a triple interaction with the *High risk* indicator for counties' disaster exposure and include time fixed effects. The triple interaction term is negative and highly statistically significant (at the 1% level). This implies that the differential impact of monetary policy on mortgage demand across low- and high-risk counties is amplified by insurers' exposure.

In columns (4) to (6), we re-estimate these regressions using the total mortgage *Amount* applied for. Again, we find that mortgage demand declines significantly more in high-risk counties when insurers are exposed to monetary policy. These results remain unchanged when we use our MTM-based ϕ (see Appendix Table 2.D.6).

Overall, these results suggest the existence of an "insurance channel" of monetary policy. This channel works through an asset-price-driven decrease in the supply of homeowners insurance, which accounts for a large share of housing

18. The fastest states, in terms of decision time, typically take less than a month for the average filing, while the slowest states need more than a quarter (see Appendix Table 2.D.5).

costs. This decrease reduces demand for homes and mortgages, particularly in disaster-exposed regions.

Table 2.8.1. Mortgage markets, insurance markets, and monetary policy

	Dependent variable: $\Delta Log(Mortgage\ outcome)_{c,y}$					
Mortgage outcome:	Mortgage applications			Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \mathrm{MP}_{Q4(y-1)}$	-1.559***	-2.739***		-1.457***	-1.571***	
	[-18.09]	[-34.74]		[-12.64]	[-12.21]	
$\phi_{s,y}$		-0.000	0.002***		-0.001*	0.002**
		[-0.30]	[2.80]		[-1.82]	[2.22]
$\phi_{s,y} \times \Delta \mathrm{MP}_{Q4(y-1)}$		-0.002	0.028		0.039	0.024
		[-0.09]	[1.13]		[1.33]	[0.76]
High risk$_{c,y}$ $\times$ $\phi_{s,y}$			-0.181***			-0.174***
$\times$ $\Delta \mathrm{MP}_{Q4(y-1)}$			[-4.32]			[-3.32]
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes		Yes	Yes	
Lag Dep. Variable	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE			Yes			Yes
No. of obs.	24,591	20,934	20,934	24,591	20,934	20,934
R^2	0.520	0.993	0.574	0.504	0.514	0.552
Within R^2	0.503	0.166	0.134	0.487	0.489	0.158

Notes: This table shows estimates for the transmission of monetary policy through insurance markets on mortgage markets. The dependent variable, $\Delta Mortgage\ outcome_{c,y}$, is the change in the natural logarithm of the outcome of mortgage markets in county c from year $y-1$ to year y. In columns (1) to (3), the outcome is the number of mortgage applications; in columns (4) to (6), the total mortgage amount applied for. $\Delta MP_{Q4(y-1)}$ is the sum of all monetary policy surprises in the 10-year U.S. Treasury yield in the fourth quarter of year $y-1$. $\phi_{s,y}$ is the sensitivity of insurers operating in state s (where county c is located) to monetary policy measured in the first month of year y. The sensitivity is constructed based on insurers' fixed income portfolio duration. We control for several lagged county-level variables, i.e., *Population density* and changes in *GDP*, *Income per capita*, and *Population*, macroeconomic controls, i.e., *ΔGDP*, *VIX*, and *ΔCPI*, and one lag of the dependent variable. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. Standard errors are clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

2.9 Conclusion

Insurance companies are important financial intermediaries between households and financial markets. Despite their pivotal role, there is a notable scarcity of evidence on how insurers contribute to macroeconomic dynamics. We contribute to this topic by documenting the impact of monetary policy on homeowners insurance prices, one of households' most essential insurance products. Consistent with a model in which regulatory-constrained insurers seek to compensate for the negative impact of monetary policy on their investment income by raising prices, we find that prices increase in response to contractionary shocks. Exploiting disaggregated data on insurers' balance sheets, we provide empirical evidence for this mechanism. As insurers suffer from the price impact of monetary policy on assets held at market values and, especially on those with a longer duration, regulatory-constrained insurers with a higher share of MTM assets and longer portfolio durations raise prices significantly more in response to contractionary policy surprises. These findings align with the model's predictions. Lastly, we show that this response in insurance supply transmits to the broader economy by affecting demand for housing. Constructing variation in insurers' ex-ante sensitivity to monetary policy, we find that home prices and mortgage demand decrease significantly more in response to monetary policy in areas that are more exposed to monetary-policy-sensitive insurers. Overall, our results emphasize the importance of the insurance sector in the aggregate economy and suggest that insurance markets significantly contribute to the transmission of monetary policy, i.e., monetary policy also works through an "insurance channel".

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Appendix 2.A Proofs

Proof. of Proposition 2

We first note that:

$$\frac{\partial}{\partial r_f}\chi_i = \chi_i' \frac{\partial K_i}{\partial r_f} \tag{2.A.1}$$

$$= \chi_i' \times \left(\alpha_i + \frac{\partial P_i}{\partial r_f} Q_i' \big(P_i - (1+\rho)\big) + Q_i \frac{\partial P_i}{\partial r_f}\right) \tag{2.A.2}$$

$$= \chi_i' \times \left(\alpha_i + P_i \big(Q_i' \big(P_i - (1+\rho)\big) + Q_i\big) \frac{\partial \log P_i}{\partial r_f}\right) \tag{2.A.3}$$

$$= \chi_i' \times \left(\alpha_i + Q_i (P_i - \epsilon_i \big(P_i - \big(1+\rho\big)\big)) \frac{\partial \log P_i}{\partial r_f}\right) \tag{2.A.4}$$

$$= \chi_i' \times \left(\alpha_i + Q_i \epsilon_i \left((1+\rho) - P_i \left(1 - \frac{1}{\epsilon_i}\right)\right) \frac{\partial \log P_i}{\partial r_f}\right) \tag{2.A.5}$$

$$= \chi_i' \times \left(\alpha_i + Q_i \epsilon_i V \left((1+\rho)e^{r_f} - \frac{1+\chi_i(1+\rho)}{1+\chi_i}\right) \frac{\partial \log P_i}{\partial r_f}\right) \tag{2.A.6}$$

and then see that:

$$\frac{\partial}{\partial r_f}\log P_i = \frac{1+\chi_i}{1+\chi_i(1+\rho)} \frac{\partial}{\partial r_f}\left(\frac{1+\chi_i(1+\rho)}{1+\chi_i}\right) + \frac{1}{V}\frac{\partial}{\partial r_f} V \tag{2.A.7}$$

$$= -1 + \frac{1+\chi_i}{1+\chi_i(1+\rho)} \left(\frac{(1+\rho)}{1+\chi_i} - \frac{1+\chi_i(1+\rho)}{(1+\chi_i)^2}\right) \frac{\partial \chi_i}{\partial r_f} \tag{2.A.8}$$

$$= -1 + \frac{1+\chi_i}{1+\chi_i(1+\rho)} \frac{\rho}{(1+\chi_i)^2} \frac{\partial \chi_i}{\partial r_f} \tag{2.A.9}$$

$$= -1 + \frac{1}{1+\chi_i(1+\rho)} \frac{\rho}{1+\chi_i} \frac{\partial \chi_i}{\partial r_f} \tag{2.A.10}$$

$$= -1 - \delta_i \times \left(\alpha_i + Q_i \epsilon_i V \left((1+\rho)e^{r_f} - \frac{1+\chi_i(1+\rho)}{1+\chi_i}\right) \frac{\partial \log P_i}{\partial r_f}\right) \tag{2.A.11}$$

$$= -\frac{1+\delta_i \alpha_i}{1+\delta_i Q_i \epsilon_i V \left((1+\rho)e^{r_f} - \frac{1+\chi_i(1+\rho)}{1+\chi_i}\right)} \tag{2.A.12}$$

□

Appendix 2.B Data

Table 2.B.1. Variable definitions and data sources

Variable	Definition (Unit)
	Filing information
ΔPrice	The effective change of the insurance price granted by the regulator in the filing. *Source: S&P Rate Watch.*
Filing time	The days between the insurer's current and last filing in the same state. *Source: S&P Rate Watch.*
Policyholders	The number of policyholders affected by the price change. *Source: S&P Rate Watch.*
Premiums written	The total premiums written by the insurer on the product subject to the filing. *Source: S&P Rate Watch.*
Minimum ΔPrice	The minimum price change requested by the insurer in the filing. *Source: S&P Rate Watch.*
Maximum ΔPrice	The maximum price change requested by the insurer in the filing. *Source: S&P Rate Watch.*
Target ΔPrice	The insurer's targeted price change indicated in the filing. *Source: S&P Rate Watch.*
	Insurer characteristics
Assets	The insurer's total assets at the end of a quarter. *Source: NAIC Regulatory Filings.*
RBC ratio	The insurer's risk-based capital ratio. *Source: NAIC Regulatory Filings.*
ROE	The insurer's annualized return on equity. *Source: NAIC Regulatory Filings.*
Leverage	The insurer's leverage. *Source: NAIC Regulatory Filings.*
UW gain	The insurer's annualized underwriting gain as a percentage of total liabilities. *Source: NAIC Regulatory Filings.*
Investment income	The insurer's annualized investment income as a percentage of total invested assets. *Source: NAIC Regulatory Filings.*
Cash flow	The insurer's annual/quarterly cash flow as a percentage of lagged cash. *Source: NAIC Regulatory Filings.*
RBC gap	The difference between the insurer's average RBC ratio over the previous six years and the insurer's current RBC ratio. *Source: NAIC Regulatory Filings.*

Table 2.B.1 continued.

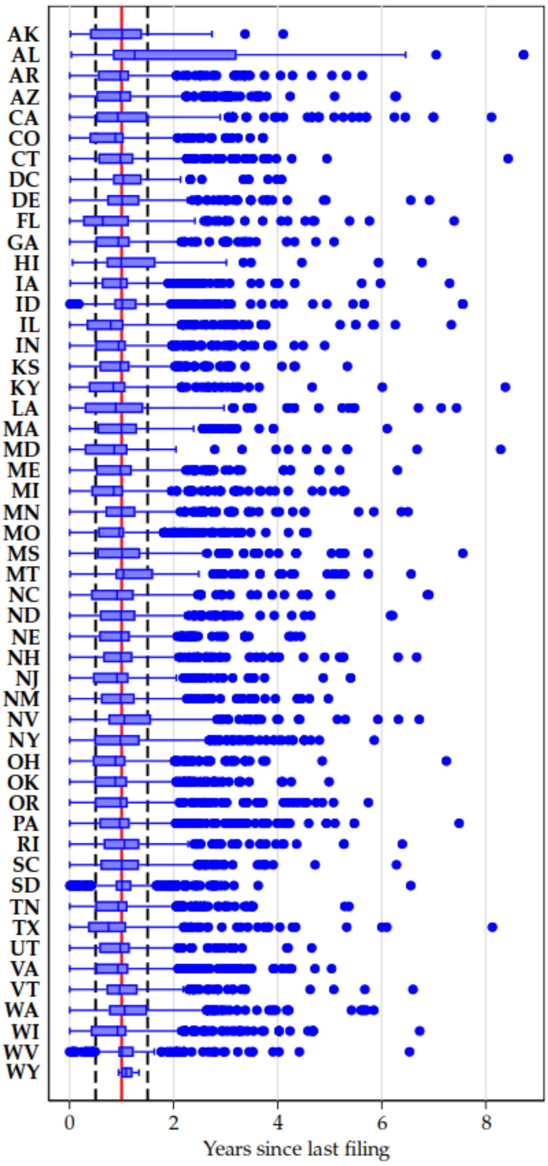
Duration	The insurer's average duration of fixed-income securities. *Source: See Appendix 2.E.*
MTM share	The insurer's share of *Assets* that is marked-to-market. *Sources: NAIC Regulatory Filings and own calculations.*
Regulatory capital	The total amount of insurer's regulatory capital. *Source: NAIC Regulatory Filings.*
	State characteristics
Mean 5-yr damage	The average yearly damage caused by natural disasters (excluding floods) in a state over the past 5 years. *Source: SHELDUS and own calculations.*
SD 5-yr damage	The standard deviation of yearly damage caused by natural disasters (excluding floods) in a state over the past 5 years. *Source: SHELDUS and own calculations.*
Income per capita	The state's annual personal income per capita. *Source: BEA.*
GDP per capita	The state's annual gross domestic product per capita. *Source: BEA.*
ΔHPI	The annual growth rate of the House Price Index in the state. *Source: FHFA.*
ϕ	Sensitivity of local insurance companies' prices to monetary policy changes. *Source: Own calculations.*
	County variables
Home value	The county's monthly Zillow Home Value Index value.*Source: Zillow.*
Mortgages	The annual number of mortgages originated in the county.*Source: HMDA.*
Amount	The annual mortgage amounts originated in the county.*Source: HMDA.*
Population	The county's annual population. *Source: Census.*
GDP	The county's annual gross domestic product. *Source: BEA.*
Income per capita	The county's annual per capita income. *Source: BEA.*
Population density	The county's population density. *Source: Own calculations.*
5-yr damages	The total damage caused by natural disasters (excluding floods) in a county over the past 5 years. *Source: SHELDUS and own calculations.*

Table 2.B.1 continued.

	Macroeconomic variables
ΔGDP	The annualized growth rate of the national real gross domestic product. *Source: FRED.*
VIX	The CBOE Volatility Index (VIX). *Source: FRED.*
ΔCPI	The annualized national inflation measured by the Consumer Price Index. *Source: FRED.*
ΔPCE	The annualized national inflation measured by the Personal Consumption Expenditures Index. *Source: FRED.*
	Monetary policy shocks
ΔMP	The high-frequency change in the 10-year US Treasury rate around FOMC meetings. *Source: Bauer and Swanson (2023).*
ΔNS	The high-frequency monetary policy shocks identified by Nakamura and Steinsson (2018). *Source: Emi Nakamura's webpage.*.
ΔTarget	The surprises in the target factor around FOMC meetings identified by Gürkaynak, Sack, and Swanson (2005). *Source: Updated shock series from Miguel Acosta's webpage.*

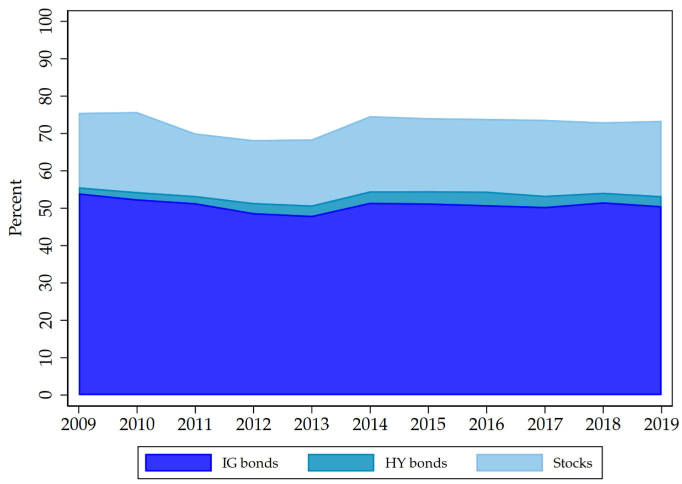
Appendix 2.C Additional Figures

Figure 2.C.1. Time between filings

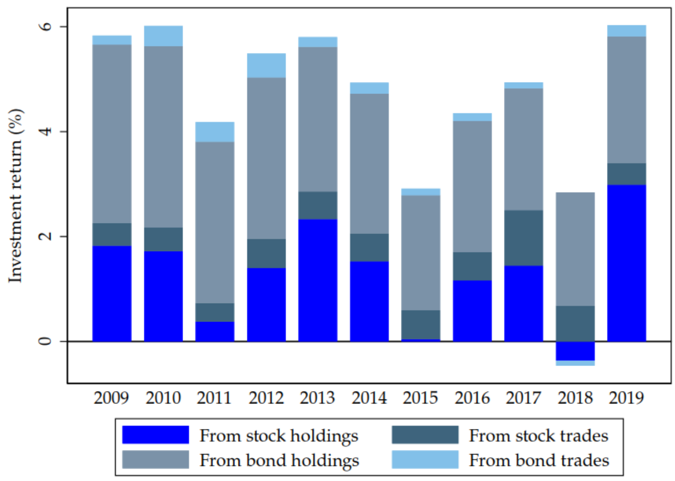


Notes: This figure shows for each state the distribution of *Filing time*, i.e., the number of years between insurers' current and the last filing in the same state. The red line marks one year since the last filing; the black dashed lines mark the times of half a year since the last filing and one and half years since the last filing.

Figure 2.C.2. Asset and investment income composition of insurers



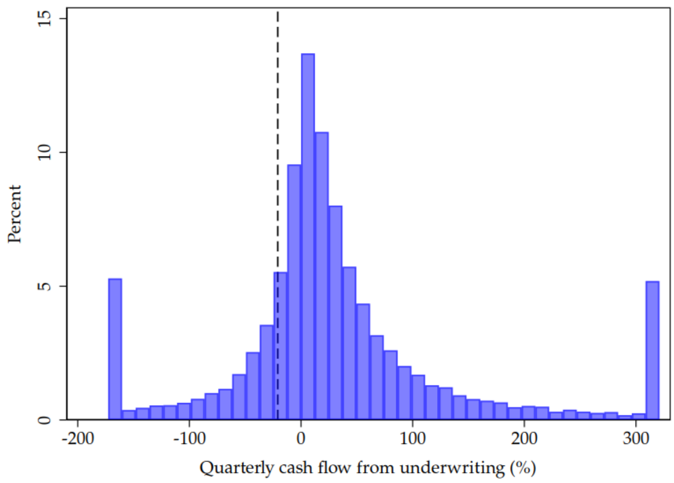
(a) Asset side composition



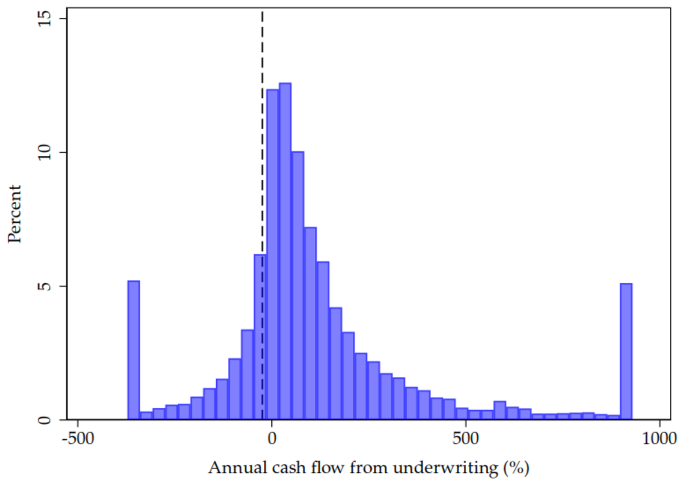
(b) Investment income composition

Notes: This figure shows (a) the asset side composition split by bond and stock holdings and (b) the investment income composition split by investment income generated from bond and stock holdings and trades of insurers over the sample period. Bond holdings and trades include all fixed-income securities, i.e., mainly corporate bonds, municipal bonds, U.S. Treasuries, and asset-backed securities.

Figure 2.C.3. Distribution of quarterly and annual cash flows from underwriting



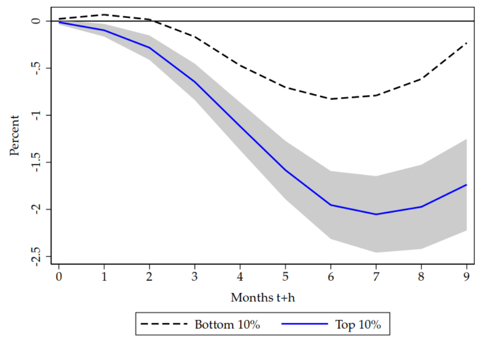
(a) Insurer-week sample



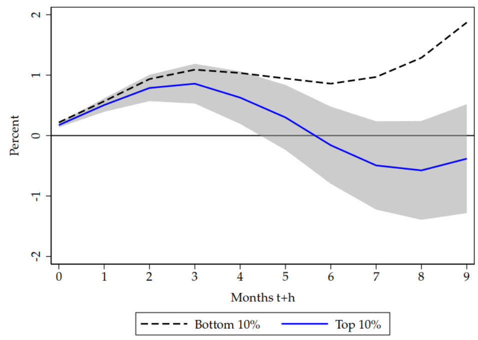
(b) Insurer-year sample

Notes: This figure shows histograms for the cash flow variable used in Table 2.6.2 and Appendix Table 2.D.4. In panel (a), it is the annual cash flow from underwriting scaled by lagged cash; in panel (b), the cash flow variable is the quarterly cash flow from underwriting scaled by lagged cash. The dotted vertical lines represent the distribution's 20th percentiles, which serve as thresholds for defining liquidity constraints.

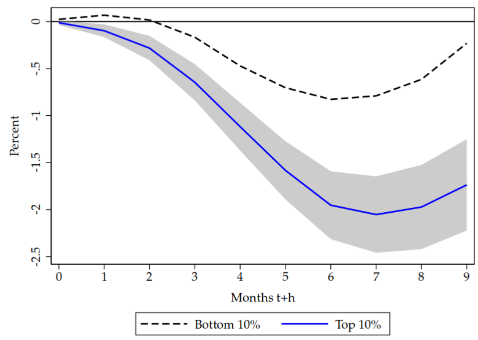
Figure 2.C.4. Robustness: Local projections with duration-based ϕ



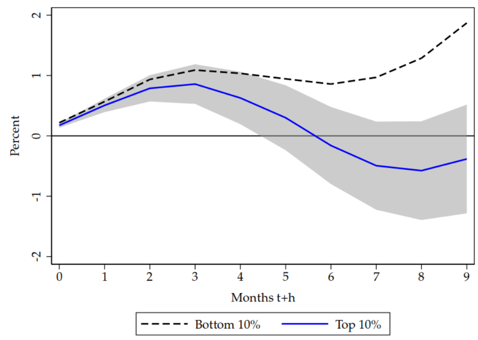
(a) Single family homes - Duration ϕ



(b) Condos - Duration ϕ



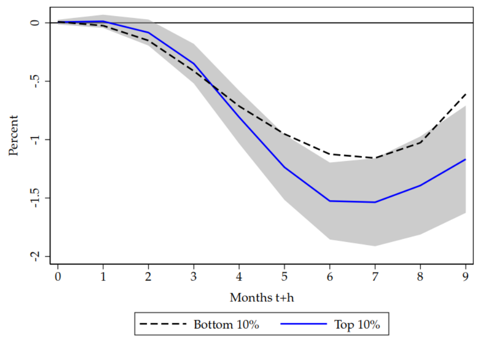
(c) Top tier - Duration ϕ



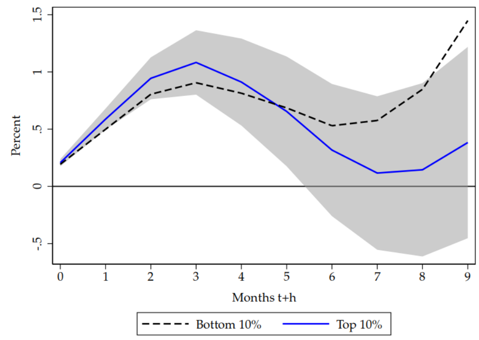
(d) Bottom tier - Duration ϕ

Notes: This figure shows the local projection of monetary policy's effect on home prices and the interaction with insurers' sensitivity for various subsectors of real estate markets. The black dashed line represents the effect of a 1 percentage point surprise in the 10-year U.S. Treasury yield over the previous six months on home prices at the 10th percentile of the pooled distribution of insurers' sensitivity. The blue solid line represents the effect at the 90th percentile of the pooled distribution of insurers' sensitivity. The gray area plots the corresponding 95% confidence intervals. Insurers' sensitivity ϕ is constructed with the duration of the insurer's bond portfolio.

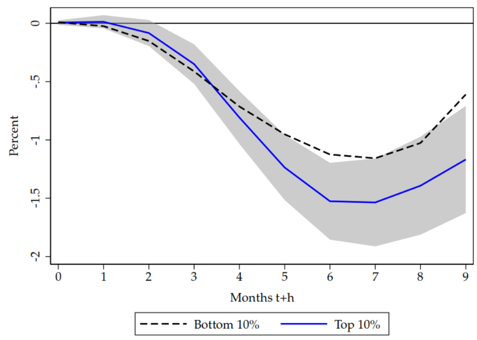
Figure 2.C.5. Robustness: Local projections with MTM share-based ϕ



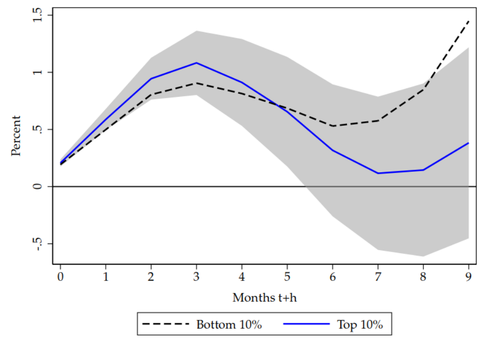
(a) Single family homes - MTM share ϕ



(b) Condos - MTM share ϕ



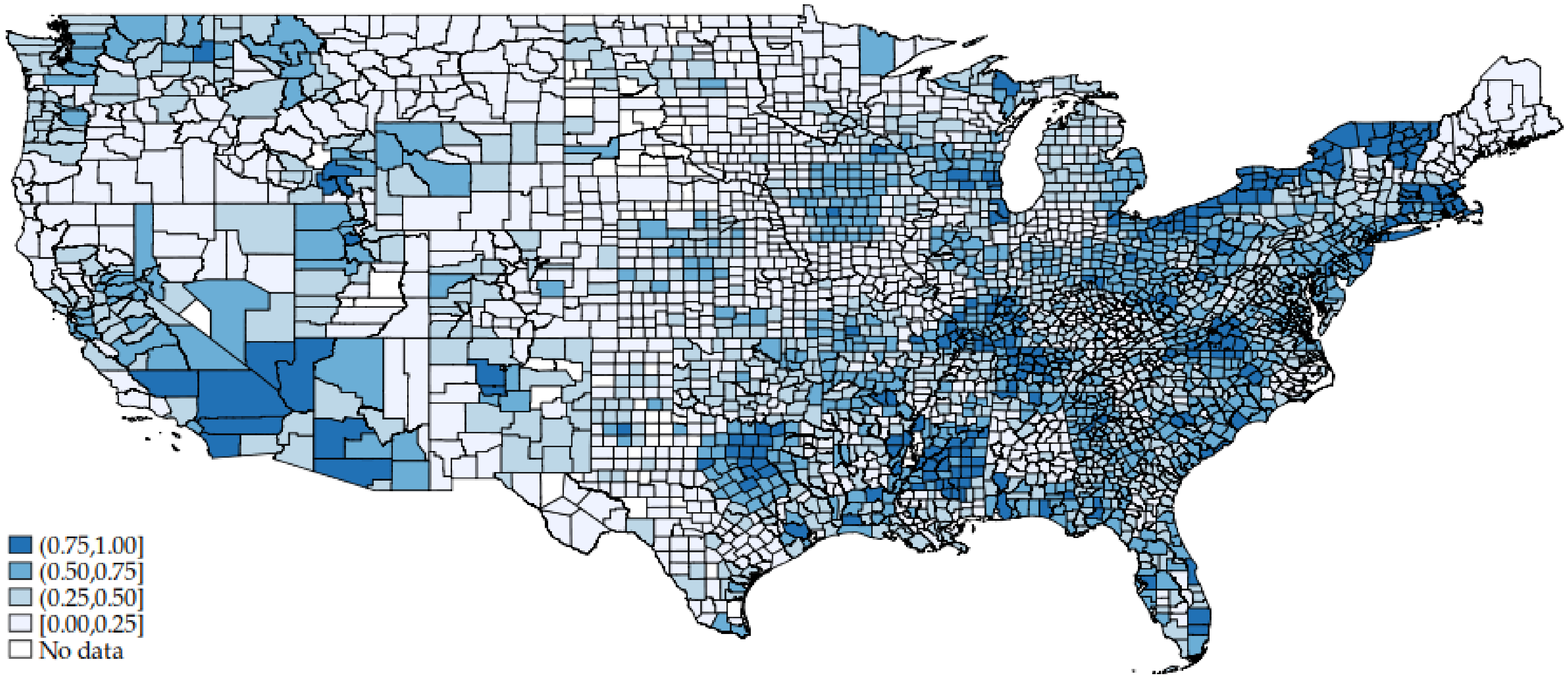
(c) Top tier - MTM share ϕ



(d) Bottom tier - MTM share ϕ

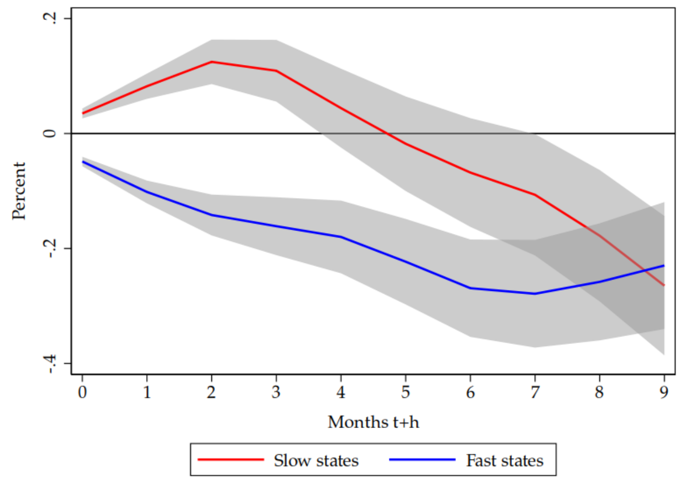
Notes: This figure shows the local projection of monetary policy's effect on home prices and the interaction with insurers' sensitivity for various subsectors of real estate markets. The black dashed line represents the effect of a 1 percentage point surprise in the 10-year U.S. Treasury yield over the previous six months on home prices at the 10th percentile of the pooled distribution of insurers' sensitivity. The blue solid line represents the effect at the 90th percentile of the pooled distribution of insurers' sensitivity. The gray area plots the corresponding 95% confidence intervals. Insurers' sensitivity ϕ is constructed with the share of insurers' assets mark-to-market.

Figure 2.C.6. Disaster exposure of U.S. counties

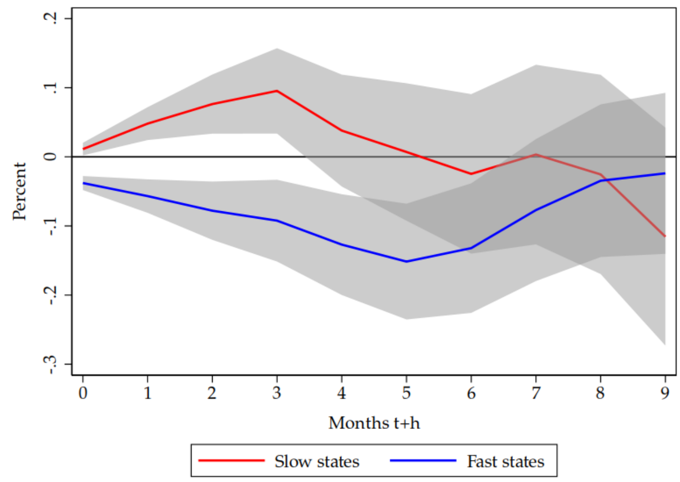


Notes: This figure shows each county's share of monthly observations between January 2010 and December 2019, where the county incurred natural disaster damages over the past 5 years.

Figure 2.C.7. Regulators' decision time and the speed of transmission



(a) Duration ϕ



(b) MTM share ϕ

Notes: This figure shows the local projection of the interaction of monetary policy and insurers' sensitivity across the regulator's decision speed. The red line represents the effect of a 1 percentage point surprise in the 10-year U.S. Treasury yield over the previous six months at the 90th percentile of the pooled distribution of insurers' sensitivity for states with slow regulators, i.e., regulators in the bottom tercile of the distribution of average decision time over the sample period. The blue line represents the effect for fast regulators, i.e., regulators in the top tercile of the distribution. The gray areas represent the 95% confidence intervals. Panel (a) shows the interaction using the duration-based measure of insurers' sensitivity to monetary policy. Panel (b) shows the interaction using the MTM share-based measure of insurers' sensitivity to monetary policy.

Appendix 2.D Additional Tables

Table 2.D.1. Cleaning procedure for the main sample

Homeowners insurance filings	165,780
Withdrawn, disapproved or other	10,658
No or missing rate change	114,737
No NAIC ID	570
Disposal date before submission date	8
Pending or reopened according to SERFF	18
First filings	6,043
Not matched to controls	6,771
Final sample	26,975

Notes: This table displays the cleaning procedure of the rate filings sample and the number of observations discarded in each step.

Table 2.D.2. Summary statistics of other variables

Panel 1: Filing information

	N	Mean	SD	1st	25th	Median	75th	99th
Policyholders (thd)	26,225	18.30	46.71	0.00	0.97	3.89	13.56	337.72
Premiums (mn USD)	25,732	17.31	41.07	0.00	0.97	3.92	13.63	279.99
Target ΔPrice (%)	21,679	17.09	16.88	-11.77	5.90	13.10	23.90	85.40

Panel 2: Insurer characteristics (insurer-quarter level)

	N	Mean	SD	1st	25th	Median	75th	99th
Leverage	8,183	58.34	14.11	8.44	51.20	60.47	68.49	81.80
ROE (%)	8,183	5.20	9.07	-21.58	0.89	5.39	10.04	33.54
UW gain (%)	8,183	-2.78	30.91	-109.03	-10.31	-0.92	4.89	106.10
Investment income (%)	8,183	3.10	1.30	0.22	2.22	3.06	4.00	6.69

Panel 3: State characteristics (state-year level)

	N	Mean	SD	1st	25th	Median	75th	99th
Mean 5-yr damages (mn USD)	549	227.47	745.93	0.20	12.20	41.91	136.12	4,227.65
SD 5-yr damages (mn USD)	549	355.94	1,349.20	0.23	10.47	45.08	155.01	8,926.89
Income per capita (thd USD)	549	45.24	8.62	31.61	39.17	43.96	49.97	71.47
GDP per capita (thd USD)	549	54.14	21.23	33.68	43.81	50.34	58.04	177.71
ΔHPI (%)	549	2.19	4.70	-11.39	-0.75	3.03	5.54	11.69

Panel 4: County characteristics (county-year level)

	N	Mean	SD	1st	25th	Median	75th	99th
Population (thd)	24,537	122.71	360.21	2.48	15.93	34.71	90.16	1,474.92
Population density	24,537	117.17	768.00	0.63	9.75	22.01	56.10	1,321.27
GDP (bn USD)	24,537	6.47	25.29	0.09	0.50	1.21	3.57	87.41
Income per capita (thd USD)	24,537	39.08	10.89	23.41	32.39	37.12	43.29	77.04

Table 2.D.2 continued.

Panel 5: Macroeconomic variables (monthly level)

	N	Mean	SD	1st	25th	Median	75th	99th
ΔGDP (%)	132	2.03	2.21	-4.40	0.81	2.22	3.44	6.38
VIX	132	18.62	7.41	10.18	13.62	16.41	21.09	44.84
ΔCPI (%)	132	0.14	0.21	-0.64	0.03	0.18	0.27	0.58

Panel 6: Insurer sensitivity (ϕ) (state-month level)

	N	Mean	SD	1st	25th	Median	75th	99th
Duration ϕ	5,999	1.00	3.02	-1.75	-0.59	0.00	1.11	11.71
MTM share ϕ	5,999	1.00	2.45	-3.30	-0.13	0.00	2.06	12.15

Notes: This table shows the summary statistics for the control variables used in the different parts of the empirical analysis.

Filing information. *Policyholders* is the number of policyholders affected by the filing. *Premiums* is the amount of premiums written in million USD on the insurance policies affected by the filing. *Target ΔPrice* is the target price change calculated by the insurer in the filing.

Insurer characteristics. *Leverage* is the insurer's leverage at the end of a quarter. *ROE* is the insurer's annualized return on equity. *UW Gain* is the insurer's annualized underwriting gain scaled by lagged total assets. *Investment Income* is the annualized net investment income scaled by lagged total invested assets.

State characteristics. *Mean 5-Yr damage* is the state's average annual damage in million USD caused by all natural disasters except floodings over the past five years. *SD 5-Yr damage* is the state's standard deviation in annual damages in million USD caused by all natural disasters except floodings over the past five years. *Income per capita* is the state's annual personal income per capita in USD. *GDP per capita* is the state's annual GDP per capita in USD. *ΔHPI* is the state's annual change in the house price index.

County characteristics. *Population* is a county's population. *Population density* is the number of inhabitants per square kilometer in a county. *GDP* is a county's annual GDP in USD. *Income per capita* is a county's annual personal income per capita in USD.

Macroeconomic variables. *ΔGDP* is the monthly growth of the U.S. gross domestic product. *VIX* is the CBOE Volatility Index. *ΔCPI* is the monthly national inflation in the Consumer Price Index.

Insurer sensitivity. ϕ is the sensitivity of insurers operating in state s in month t to monetary policy. The sensitivity is constructed based on the duration of insurers' fixed income portfolio or the share of insurers' assets mark-to-market.

Table 2.D.3. Robustness: Monetary policy and insurance prices

	Dependent variable: $\Delta Price_f$										
	Sample windows		Inflation controls			Other filing variables			Extensive margin		
Specification:	Post 2009	Post 2011	PCE	U.S. states	MP horizon	$P'holders_f$	$Premiums_f$	$Target\ \Delta Price_f$	$\mathbf{1}(Rate\ filing_{i,s,t})$	$\mathbf{1}(Filing_{i,s,t})$	$\Delta Price_{i,s,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\Delta \text{MP}_{(t-1:t-6)}$	4.329**	5.174***	3.786**	3.767**		0.225	0.224*	7.404**			0.341**
	[2.58]	[2.89]	[2.31]	[2.21]		[1.62]	[1.85]	[2.05]			[2.30]
$\Delta \text{MP}_{(t-1:f_{-1})}$					0.324***						
					[3.01]						
$\lvert\Delta \text{MP}_{(t-1:t-6)}\rvert$									-0.023	-0.008	
									[-0.90]	[-0.30]	
Insurer Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
State-Season FE									Yes	Yes	Yes
No. of obs.	26,320	21,165	26,975	16,605	26,972	25,651	25,708	21,501	362,960	362,960	362,960
R^2	0.351	0.400	0.344	0.358	0.345	0.804	0.829	0.489	0.043	0.042	0.032
Within R^2	0.058	0.075	0.055	0.065	0.056	0.029	0.057	0.060	0.019	0.018	0.014

Notes: This table shows robustness checks for the relationship between monetary policy and changes in insurance prices. In columns (1) to (5), the dependent variable $\Delta Price_f$ is the effective insurance price change of filing f. In columns (6) to (8), we examine the impact of monetary policy on other variables of insurers' rate filings. In column (6), $P'holders_f$ is the natural logarithm of the number of policyholders affected by the rate change of filing f. In column (7), $Premiums_f$ is the natural logarithm of the premiums written on the insurance policies affected by the rate change of filing f. In column (8), $Target\ \Delta Price_f$ is the target price change calculated by the insurer in filing f. In columns (9) to (11), we employ regression equation (2.5.2) in an insurer-state-month panel with three different dependent variables. In column (9), $\mathbf{1}(Rate\ filing_{i,s,t})$ is an indicator variable taking the value 1 if insurer i submits a rate filing in state s in month t. In column (10), $\mathbf{1}(Filing_{i,s,t})$ is an indicator variable taking the value 1 if insurer i submitted any filing in state s in month t. In column (11), $\Delta Price_{i,s,t}$ is the average effective price change of all rate filings submitted by an insurer in state s in month t. Price changes are weighted by the premiums written on products affected by the rate filing. In columns (1) to (3), (6) to (8), and (11) [(9) and (10)], the independent variable, $\Delta \text{MP}_{(t-1:t-6)}$ [$\lvert\Delta \text{MP}_{(t-1:t-6)}\rvert$], is the [absolute value of the] sum of all monetary policy surprises in the 10-year U.S. Treasury yield in the six months preceding the month the filing was submitted. In column (5), the independent variable, $\Delta \text{MP}_{(t-1:f_{-1})}$, is the sum of all surprises from the month of the insurer's last filing until the month preceding the same filing in the same state. We control for several lagged insurer-level variables, i.e., *Log(Assets)*, *Leverage*, *RBC ratio*, *ROE*, *UW gain*, and *Investment income*, lagged state-level variables, i.e., *Log(Mean 5-yr damage)*, *Log(SD 5-yr damage)*, *Log(Income per capita)*, *Log(GDP per capita)*, and *ΔHPI*, and macroeconomic variables, i.e., *ΔGDP*, *VIX*, and *ΔCPI*. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. All continuous insurer-level variables are winsorized at the 1% and 99% levels. Standard errors are three-way clustered at the insurer, the state, and the year-month level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.D.4. Robustness: Insurers' realized gains and monetary policy

Dep. variable:	$Gains_{i,w} - \frac{1}{3}\sum_{j=1}^{3} Gains_{i,w-j}$		
	(1)	(2)	(3)
$\Delta\text{MP}_{(w-1:w-2)}$	-0.027***	-0.021**	-0.020**
	[-3.35]	[-2.16]	[-2.28]
High $\text{duration}_{i,y(w)-1}$			-0.000
			[-0.02]
High $\text{duration}_{i,y(w)-1} \times \Delta\text{MP}_{(w-1:w-2)}$			-0.035**
			[-2.05]
Low $\text{CF}_{i,q(w)-1}$		-0.001	
		[-1.39]	
Low $\text{CF}_{i,q(w)-1} \times \Delta\text{MP}_{(w-1:w-2)}$		-0.026*	
		[-1.83]	
Insurer Controls	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes
No. of obs.	107,489	103,001	106,476
R^2	0.009	0.009	0.009
Within R^2	0.001	0.001	0.001

Notes: This table estimates the high-frequency impact of monetary policy on insurers' realized gains across liquidity shocks and fixed-income portfolio duration. The dependent variable is the change in percentage points in insurer *i*'s investment return (realized investment income) in week *w* relative to the mean realized investment income in the prior three weeks $w-3$ to $w-1$. The main independent variable, $\Delta MP_{(w-1:w-2)}$, is the sum of all monetary policy surprises in the 10-year U.S. Treasury yield in the preceding two weeks. *High* $duration_{i,y(w)-1}$ is an indicator variable that takes the value 1 if insurer *i*'s fixed income portfolio duration in year $y(w)-1$ is in the fifth quintile of the annual cross-sectional distribution of this variable. *Low* $CF_{i,q(w)-1}$ is an indicator variable that takes the value 1 if the insurer *i*'s cash flow from underwriting in quarter $q(w)-1$ scaled by lagged holdings is in the fifth quintile of the cross-sectional distribution of this variable. We control for several lagged insurer-level variables, i.e., *Log(Assets)*, *Leverage*, *RBC ratio*, *ROE*, *UW gain*, and *Investment income*, and macroeconomic variables, i.e., *ΔGDP*, *VIX*, and *ΔCPI*. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. All continuous insurer-level variables are winsorized at the 1% and 99% levels. Standard errors are two-way clustered at the insurer and the week level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.D.5. State-level information on insurance markets

	# Filings	# Insurers	Mean decision time (# days)	Mean *ΔPrice*(%)
Alabama	59	17	130.29	4.63
Alaska	78	11	60.33	5.63
Arizona	763	101	11.04	5.3
Arkansas	536	69	26.16	7.91
California	313	55	191.34	5.94
Colorado	947	97	202.86	7.68
Connecticut	619	89	93.83	5.26
Delaware	279	51	79.73	5.72
District Of Columbia	139	27	118.94	4.39
Florida	601	70	101.02	6.14
Georgia	844	112	61.92	8.79
Hawaii	54	11	132.81	6.16
Idaho	382	61	59.03	5.77
Illinois	1259	133	27.9	5.17
Indiana	859	117	42.55	4.81
Iowa	717	90	13.98	6.75
Kansas	660	87	27.19	6.79
Kentucky	710	81	16.31	5.9
Louisiana	402	63	53.94	5.71
Maine	415	60	25.91	4.9
Maryland	189	45	126.94	4.81
Massachusetts	599	92	105.18	3.94
Michigan	642	73	33.37	4.71
Minnesota	587	97	63.99	6.29
Mississippi	370	54	83.44	7.57
Missouri	853	100	45.98	6.3
Montana	295	54	40.68	7.61
Nebraska	600	83	41.96	8.87
Nevada	320	56	60.33	4.88
New Hampshire	450	72	40.46	4.82
New Jersey	645	93	41.63	4.61
New Mexico	382	59	12.73	7.62
New York	670	110	76.76	3.41
North Carolina	426	55	19.86	4.03
North Dakota	361	52	38.65	4.79
Ohio	1096	126	38.56	5.6
Oklahoma	751	87	33.47	8.37
Oregon	509	76	28.89	5.02
Pennsylvania	805	124	33	5.49
Rhode Island	328	57	94.54	6.83
South Carolina	554	88	76.72	6.5
South Dakota	428	62	16.22	8.56
Tennessee	861	112	30.07	6.89
Texas	600	74	94.88	5.86
Utah	366	63	32.96	5.45
Vermont	279	46	37.22	3.26
Virginia	873	110	44.75	5.19
Washington	363	65	95.22	5.26
West Virginia	269	43	58.76	7.06
Wisconsin	860	111	2.52	5.53
Wyoming	8	1	43.13	6.32

Notes: This table displays information on the insurance markets and regulators of the 51 U.S. states in our filing-level sample. *# Filings* is the number of rate filings in the state over the sample period. *# Insurers* is the number of insurers that submitted at least one filing in the state over the sample period. *Mean decision time (# days)* is the average number of days between the submission and the approval of a rate filing in the state. *Mean ΔPrice* is the average effective price change of a rate filing in the state over the sample period.

Table 2.D.6. Robustness: Mortgage markets, insurance markets, and monetary policy

	Dependent variable: *ΔLog(Mortgage outcome)*$_{c,y}$					
Mortgage outcome:	Mortgage applications			Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \mathrm{MP}_{Q4(y-1)}$	-1.559***	-1.573***		-1.457***	-1.503***	
	[-18.09]	[-16.34]		[-12.64]	[-11.63]	
$\phi_{s,y}$		0.002**	0.002***		0.001	0.001
		[2.11]	[2.81]		[1.06]	[0.57]
$\phi_{s,y} \times \Delta \mathrm{MP}_{Q4(y-1)}$		-0.046*	0.071**		-0.036	0.104***
		[-1.66]	[2.21]		[-1.01]	[2.61]
High risk$_{c,y} \times \phi_{s,y}$			-0.260***			-0.235***
$\times \Delta \mathrm{MP}_{Q4(y-1)}$			[-4.58]			[-3.41]
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes		Yes	Yes	
Lag Dep. Variable	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE			Yes			Yes
No. of obs.	24,591	20,934	20,934	24,591	20,934	20,934
R^2	0.520	0.534	0.575	0.504	0.514	0.552
Within R^2	0.503	0.509	0.135	0.487	0.489	0.158

Notes: This table shows estimates for the transmission of monetary policy through insurance markets on mortgage markets. The dependent variable, *ΔMortgage outcome*$_{c,y}$, is the change in the natural logarithm of the outcome of mortgage markets in county c from year $y-1$ to year y. In columns (1) to (3), the outcome is the number of mortgage applications; in columns (4) to (6), the total mortgage amount applied for. $\Delta MP_{Q4(y-1)}$ is the sum of all monetary policy surprises in the 10-year U.S. Treasury yield in the fourth quarter of year $y-1$. $\phi_{s,y}$ is the sensitivity of insurers operating in state s (where county c is located) to monetary policy measured in the first month of year y. The sensitivity is constructed based on the share of insurers' assets mark-to-market. We control for several lagged county-level variables, i.e., *Population density* and changes in *GDP*, *Income per capita*, and *Population*, macroeconomic controls, i.e., *ΔGDP*, *VIX*, and *ΔCPI*, and one lag of the dependent variable. All variables are defined in Table 2.4.1 and Appendix Table 2.D.2. Standard errors are clustered at the county level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Appendix 2.E Calculating Bond Durations

2.E.1 Constructing the Duration Measure

We compute the end-of-year duration for the universe of insurers' fixed-income securities (reported in NAIC Schedule D Part 1). The Macaulay duration of an asset is defined as,

$$\text{Duration}_{b,t} = \left[\sum_{j=1}^{n} \frac{j \times C_{b,j}}{(1+y_{b,t})^j}\right] \Big/ P_{b,t}, \tag{2.E.1}$$

where $C_{b,j}$ is the cash flow from asset b received at time $j > t$, $y_{b,t}$ is the appropriate discount rate for asset b at time t, and $P_{b,t}$ is the market price of asset b at time t. We collect information on the payment schedule of the asset, maturity date, coupon rate, discount rates, and market prices from the following data sources.

- **Mergent FISD:** The data set contains issue-level information on corporate bonds, U.S. Treasuries, and some asset-backed securities. We retrieve information on bonds' coupon rates, maturity dates, and bond features.
- **TRACE Enhanced:** The data set contains all corporate bond transactions in the U.S. market. We use the data to calculate market prices for corporate bonds after applying the cleaning procedure from Dick-Nielsen (2009) and Dick-Nielsen (2014).
- **MSRB:** The data set contains all municipal bond transactions in the U.S. market. We use the data to calculate market prices for municipal bonds.
- **Federal Reserve :** The Fed calculates daily U.S. Treasury yields based on the procedure in Gürkaynak, Sack, and Wright (2007). We access the data via federalreserve.gov.

Where we can obtain all necessary information, we directly compute the Macaulay duration. For municipal bonds, we assume a semiannual coupon payment as this is the most common form of payment structure among municipal bonds (msrb.org). All Treasury securities, i.e., notes and bonds, generally pay interest on a semiannual basis (treasurydirect.gov).

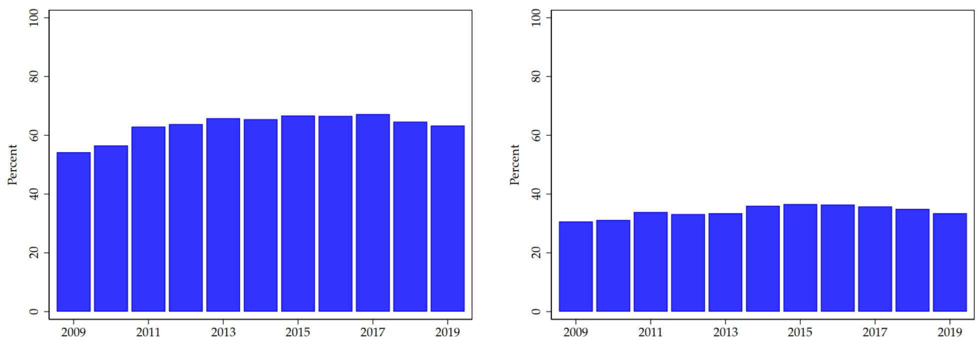
When we lack information on the payment schedule, we infer durations from assets with a similar rating and coupon structure. To do so, we cluster all bond-year observations into a year-rating-coupon-time to maturity (TTM) grid defining three buckets for ratings, i.e., "Prime/High grade", "Medium grade", and "Speculative/default", and three buckets for coupon rates, i.e., $[0\%, 4\%)$, $[4\%, 6\%)$, and $> 6\%$. The grid includes all TTMs from 0 to the maximum years available. Using the calculated durations from the first step, we then calculate the average bond duration for each cluster and assign it to the bonds lacking information on the payment schedule (except municipal bonds). We require at least 5 observations in a bucket to calculate the average. For the remaining buckets, we impute the duration by estimating for each year-rating-coupon bucket the regression,

$$\text{Duration}_b \;=\; \beta_1 \times \text{TTM}_b + \beta_2 \times \text{TTM}_b^2 + \epsilon_b, \tag{2.E.2}$$

where $Duration_b$ is the duration of bond b, and TTM_b is the remaining time to maturity of bond b in years. We merge the estimates $\{\hat{\beta}_1, \hat{\beta}_2\}$ from equation 2.E.2 to the year-rating-coupon buckets and interpolate values for the different bonds.

This procedure allows us to compute durations for more than 1.01 million (1.52 million) bond-year observations from 2009 to 2019 (2006 to 2020). Our duration measure matches around 60 percent of insurers' fixed income portfolio - mainly corporate bonds, U.S. Treasuries, and municipal bonds - and more than 30 percent of insurers' total assets.

Figure 2.E.1. Match of duration measure with insurers' portfolios and assets



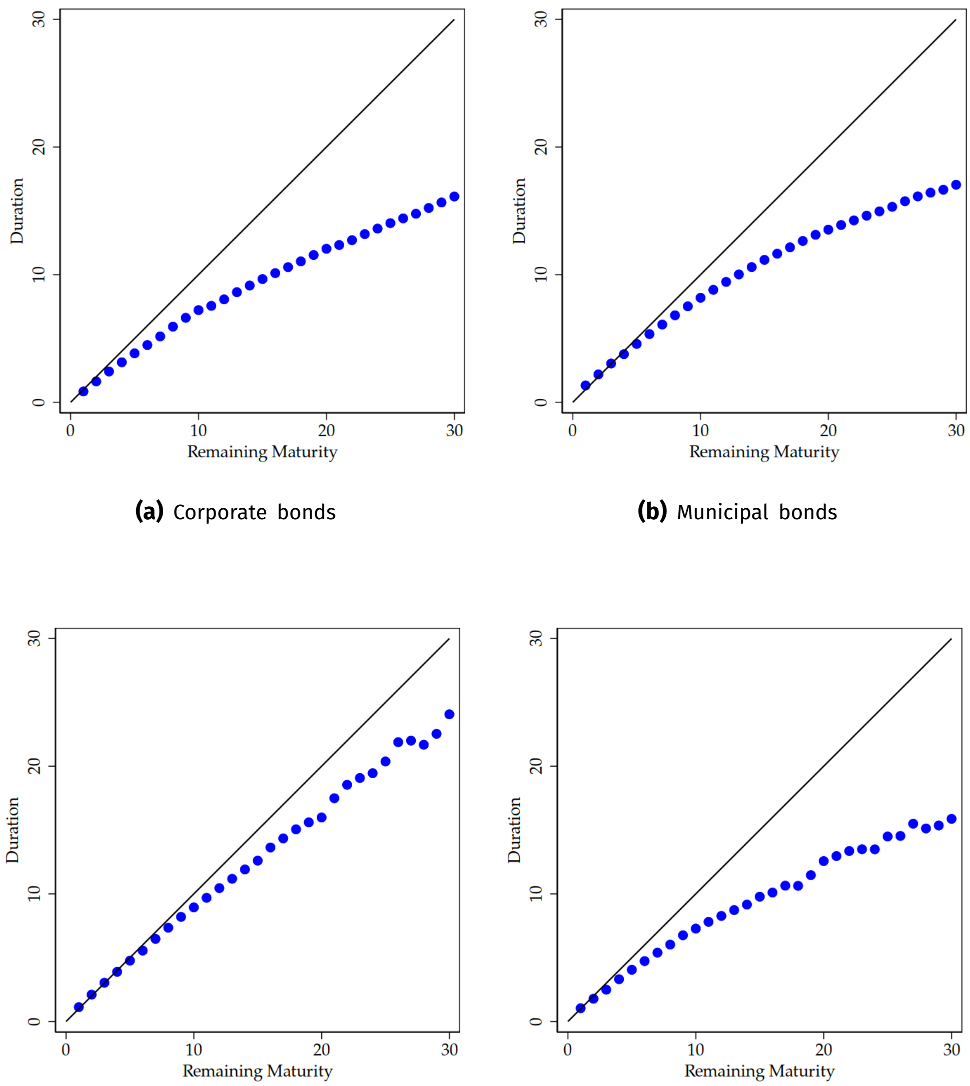
(a) Fixed income portfolio **(b)** Total assets

Notes: This figure shows (1) the aggregate share of insurers' fixed income portfolio and (2) the aggregate share of total assets matched with our duration measure between 2009 and 2019.

2.E.2 Validation of the Duration Measure

To validate our duration measure, we first compare it to the remaining maturity of the asset. We consider the main asset categories (as defined by the NAIC) for which we can calculate the Macaulay duration: corporate bonds, municipal bonds, U.S. Treasuries, and foreign bonds. Figure 2.E.2 shows the relationship between the remaining time to maturity and the Macaulay duration of the asset categories. The black line represents the $x = y$ line. The figure shows that our duration measure behaves as expected from a Macaulay duration. For short-term assets, the duration is almost the same as the remaining maturity. However, with increasing maturity, the duration measure diverges from the remaining maturity and is substantially shorter than the remaining maturity (for long-term assets). Furthermore, comparing the different asset classes shows that the gap between duration and remaining maturity is the largest for corporate bonds, the smallest for U.S. Treasuries, and in between for municipal bonds. This aligns with the intuition that corporate bonds have a higher yield and, thus, a lower duration than U.S. Treasuries.

Figure 2.E.2. Relationship between remaining maturity and duration



(a) Corporate bonds

(b) Municipal bonds

(c) U.S. Treasuries

(d) Foreign bonds

Notes: This figure shows the relationship between the remaining time to maturity and the Macaulay duration of the asset categories for which we can calculate the Macaulay duration. We follow the asset categories defined in the NAIC Schedule D regulatory filings of insurers. The black line represents the $x = y$ line.

To further check the validity of our duration estimates, we estimate the relationship between bond returns and bond duration. For this purpose, we calculate monthly bond returns,

$$R_{b,m} = \frac{P_{b,m} - P_{b,m-1}}{P_{b,m-1}} \tag{2.E.3}$$

where $P_{b,m}$ is the price of bond b in month m. To calculate returns, we construct bonds' monthly prices from Trace Enhanced after applying the cleaning procedure laid out in Dick-Nielsen (2009) and Dick-Nielsen (2014). We then estimate the following regression model,

$$\begin{aligned} R_{b,m} = {} & \alpha + \beta\ \Delta\text{MP}_{m-1} \times \text{Duration}_{b,y(m)-1} + \gamma\ \Delta\text{MP}_{m-1} \\ & + \delta\ \text{Duration}_{b,y(m)-1} + u_b + \varepsilon_{b,m}, \end{aligned} \tag{2.E.4}$$

where $R_{b,m}$ is the return of bond b from month $m-1$ to month m. $\Delta\text{M.P.}_{t-1}$ is the sum of changes in the 10-year U.S. Treasury yield around a 30-minute window of FOMC meetings taken from Bauer and Swanson (2023). $\text{Duration}_{b,y(m)-1}$ is our calculated Macaulay duration of bond b at the end of the preceding year. To exploit only the time series of bonds, we include bond fixed effects and cluster standard errors at the bond level. To be valid, the interaction of monetary policy shocks and duration measures must be negative and significant, as bonds with a higher duration react more strongly to monetary policy.

Table 2.E.1 shows the results of our validation exercise. In the first three columns, we calculate returns based on median prices of bonds in a month for a sample period from January 2009 to December 2019, i.e., the sample period we consider in our main analysis. The results confirm the validity of our duration measure. First, monetary policy negatively affects bond returns, and second, the effect is stronger for bonds with a higher duration. In column (4), we additionally include the years 2007 to 2008, the years of the financial crisis. The results stay the same. In columns (5) and (6), we repeat regression 2.E.4 for both sample periods using this time the average price in a month to calculate the returns. Again, the interaction between our duration measure and the monetary policy shock is negative and highly significant. Overall, we conclude that our duration estimates are valid and can be used to analyze the impact of monetary policy on insurance companies' asset portfolios.

Table 2.E.1. Monetary policy, duration, and asset prices

	Dependent variable: $R_{b,m}$					
Price variable:	Median price				Average price	
Sample period:	2009:M1-2019:M12			2006:M1-2019:M12	2009:M1-2019:M12	2006:M1-2019:M12
	(1)	(2)	(3)	(4)	(5)	(6)
ΔMP_{m-1}	-9.516***	-8.996***	-1.929**	-1.620	-1.460**	-0.833
	[-15.64]	[-15.39]	[-2.00]	[-1.55]	[-2.32]	[-1.39]
$\text{Duration}_{b,y(m)-1}$	0.146***	0.116***	0.117***	-0.046***	0.115***	-0.042***
	[29.23]	[19.21]	[19.47]	[-8.17]	[20.45]	[-7.77]
$\text{Duration}_{b,y(m)-1} \times \Delta MP_{m-1}$	-0.433***	-0.550***	-0.313***	-0.160**	-0.258***	-0.146***
	[-6.14]	[-7.89]	[-4.43]	[-2.38]	[-4.63]	[-2.65]
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes	Yes
ΔMP_{m-1} × Controls			Yes	Yes	Yes	Yes
No. of obs.	1,000,808	789,995	789,995	899,405	789,995	899,405
R^2	0.086	0.125	0.128	0.055	0.105	0.057
Within R^2	0.009	0.015	0.018	0.019	0.018	0.019

Notes: This table shows estimates for the relationship between bond returns, monetary policy, and bond duration. The dependent variable, $R_{b,m}$, is the monthly return of bond b from month $m-1$ to month m. The main independent variable, ΔMP_{m-1}, is the sum of all surprises in the 10-year U.S. Treasury rate in month m. $Duration_{b,y(m)-1}$ is the Macaulay duration of bond b at the end of year $y(m)-1$. The dependent variable is the monthly return of bond b from month $m-1$ to month m. In columns (1) to (4), we calculate the return based on the median price of bond b in month m and $m-1$; in columns (5) and (6), we calculate the return based on the average price of bond b in month m and $m-1$. We include bond-level controls in columns (3) to (6). More specifically, we control for the natural logarithm of a bond's monthly trade volume and the average Bid-Ask spread. Standard errors are clustered at the bond level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

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Chapter 3

Investors' Demand for Corporate Bonds in Response to Monetary Policy: Spillovers to the Loan Market

Joint with Marcel Brambeer

3.1 Introduction

Institutional investors are the most important investor group in the U.S. corporate bond market. As such, changes in their bond demand considerably impact asset prices and firms' financing conditions (Koijen, Richmond, and Yogo, 2019; Kubitza, 2023). In particular, institutional investors' portfolios determine to a large degree how aggregate fluctuations propagate to borrowing costs and quantities (Coppola, 2022; Zhou, 2024).

Crucially, corporate bond investors compete with creditors from the loan market to provide long-term debt to firms. Bonds account for more than two-thirds of long-term debt in the financing structure of U.S. publicly traded firms, thereby bearing significant influence on the dynamics of the loan market (Berg, Fabisik, and Sautner, 2021). Against this background, aggregate shocks such as monetary policy changes that affect the corporate bond market generate repercussions to loan market outcomes (Becker and Ivashina, 2014; Grosse-Rueschkamp, Steffen, and Streitz, 2019). Indeed, monetary policy has the potential to spur the bond market activity of large bond investors. This raises the question to what extent differences in institutional investors' demand for corporate bonds are relevant for the monetary transmission to loan markets.

This paper investigates how differences in bond demand between the two largest U.S. corporate bond investors, insurers, and mutual funds shape the monetary transmission to the loan market. Using detailed regulatory data on corporate bond investments of U.S. insurers and mutual funds, we show that changes in the monetary policy stance differentially affect these two investor groups' bond demand. The relative exposure of firms to these differential demand changes depends on their investor composition. We leverage variation in the investor composition of nonfinancial firms to identify spillovers to lending markets, employing transaction-level data on syndicated loans. Conditional on monetary policy changes, we find that firms with a relatively higher demand for their bonds have a relatively higher probability of taking out a new syndicated loan.

In 2017, insurers and mutual funds accounted for about 68 percent of U.S. corporate bond holdings of domestic investors.[1] Differences in the sensitivity of bond holdings of insurers and mutual funds to aggregate fluctuations have been attributed to a large extent to the liability structure of these institutions. For example, life insurers underwrite long-term contracts, such as variable annuities with embedded surrender charges, whose contractual features disincentivize policyholders to withdraw their capital (Ozdagli and Wang, 2019; Kubitza, Grochola, and Gründl, 2023). As such, insurers can absorb aggregate shocks and ride out short-term fluctuations (Chodorow-Reich, Ghent, and Haddad, 2021). On the other hand, open-ended mutual funds allow clients to redeem their investments freely, making them prone to sudden outflows (Goldstein, Jiang, and Ng, 2017; Banegas, Montes-Rojas, and Siga, 2022; Coppola, 2022). Differences in demand sensitivities between investor types might also result from heterogeneous asset exposures to monetary policy, particularly quantitative easing (Chodorow-Reich, 2014a).

In turn, differences in the sensitivity of bond demand across investor types to monetary policy surprises heterogeneously affect firms, depending on their investor base. There are two main mechanisms for how this generates spillovers to the loan market. First, nonfinancial firms exposed to bond market activity of bond investors may strategically adjust their demand for loans. Second, creditors in the loan market may monitor movements of bond demand for specific firms and may choose to modify their lending offers to these firms. Financial institutions that grant loans to these firms compete with bond investors and may vary their profit margins or contractual conditions on loans to retain their customers.

To empirically establish the effect of monetary policy on institutional investors' corporate bond demand, we build a panel at the security level of outstanding bonds held by insurers and mutual funds from 2010 Q3 to 2019 Q2. We take high-frequency surprises in the 10-year U.S. Treasury yield from Bauer and Swanson (2023) and use these as an instrument for the 10-year U.S. Treasury yield to identify exogenous variation in the stance of monetary policy. A key challenge that threatens the causal interpretation of investors' demand is the confounding

1. Source: Z.1 Financial Accounts of the United States, release Table L.213, of the Board of Governors of the Federal Reserve System. Note that these statistics explicitly exclude foreign investors.

influence of monetary policy on bond supply. Moreover, time-varying issuer fundamentals are essential to investors' portfolio allocations. We address these concerns by including security-time fixed effects, i.e., we exploit exclusively variation in bond ownership over time within each security (Khwaja and Mian, 2008). We find that an increase in the 10-year yield induced by monetary policy leads to a stronger decrease in the bond investment of mutual funds compared to insurers. This effect is robust to various specifications. Mutual funds scaling down more on existing bond holdings than insurers drive this first result. Moreover, we document a stronger decrease in mutual funds' bond demand relative to insurers, particularly among bonds with maturities between 3 and 10 years and high-yield bonds.

Building upon these first results, we construct firm-specific proxies for demand changes resulting from monetary policy changes. More specifically, we use the difference in growth rates of insurers' and mutual funds' aggregate corporate bond holdings to measure differential aggregate demand changes. Further, we interact this measure with the share of a firm's outstanding bonds, which insurers hold. This share quantifies the firm's exposure to the differential demand changes of insurers and mutual funds. We then extend our analysis to the loan level and test whether variation in the firm-specific proxy for demand changes affects the relative probability of firms with different bondholders taking out loans. To ensure that insurers' and mutual funds' demand changes originate from monetary policy changes, we instrument the difference in growth rates of their holdings with surprises in the 10-year U.S. Treasury yield. Yet, the share of bonds held by insurers might correlate with unobserved factors that also affect loan market outcomes, such as firm characteristics or firm-lender relationships. In particular, firms with different characteristics may respond differently to monetary policy surprises. We address this concern by including a rich set of fixed effects, such as industry-time and firm-lender fixed effects, and numerous control variables at the firm level. As lenders grant loans to multiple firms within a quarter, we can control for firm-invariant changes in loan supply through lender-time fixed effects (Khwaja and Mian, 2008). Therefore, we exclude the possibility that direct lending channels of monetary policy drive our results (Bernanke and Blinder, 1992; Jiménez, Ongena, Peydró, and Saurina, 2012; Rodnyansky and Darmouni, 2017; Elliott, Meisenzahl, Peydró, and Turner, 2022). We obtain robust negative spillovers of bond demand on firms' loan demand. A firm that experiences a higher demand for its bonds relative to other firms - sparked by monetary policy - is relatively less likely to negotiate a new loan in the subsequent period.

We perform additional empirical tests to uncover the drivers of our main result. The negative effect of higher relative bond demand on firms' loan demand pertains to nonbank and bank lenders and across different types of loans, e.g., term loans and credit lines. However, consistent with our findings in the first step, the effect is more pronounced for firms with average bond maturity between 3 and 10 years and those with high-yield bonds.

Our findings give insights into institutional investors' relevance to monetary policy transmission. We support prior evidence that the effects of institutional investors' demand go beyond pure price changes in one market and generate spillovers to other competing financial markets, emphasizing the role of institutional investors as a transmission channel of monetary policy.

Related Literature. Previous studies emphasize the role of insurers' special characteristics, i.e., investors with long-duration liabilities and preferences for specific asset maturities, in the context of monetary policy transmission (Ozdagli and Wang, 2019; Vayanos and Vila, 2021; Li, Wang, and Yu, 2023). In contrast, mutual funds' role is predominantly characterized by their scale of in- and outflows, whereas outflows (inflows) are shown to be larger after a monetary contraction (loosening) (Banegas, Montes-Rojas, and Siga, 2022; Ciminelli, Rogers, and Wu, 2022; Kaufmann, Leyva, and Storz, 2023). Furthermore, several studies have shown that institutional investors' behavior affects firms' financing conditions and investment decisions (Zhu, 2021; Coppola, 2022; Kubitza, 2023). Our result that mutual funds decrease their corporate bond holdings more than insurers during monetary tightening cycles is in line with the work by (Fang, 2023), and, similar to his approach, we then exploit firm heterogeneity in the investor composition. In contrast to Fang (2023), who assesses effects on firms' bond financing and investment, our analysis focuses on spillovers of bond demand on firms' loan demand.

Old and recent literature documents various determinants that govern the firms' substitution between bonds and loans (Rajan, 1992; Becker and Ivashina, 2014; Schwert, 2020). For example, while banks might be better at monitoring firms and offer easier renegotiation of loans in case of default, bonds provide the possibility to borrow at longer horizons since the maturity of bonds is typically longer than the maturity of loans. Moreover, Becker and Josephson (2016) show that the firms' substitution between the two debt instruments is contingent on the stance of monetary policy. In turn, the ratio of bonds and loans shapes the monetary transmission to firms' investment and market value (Crouzet, 2021; Darmouni, Siani, and Xiao, 2022).

To the extent that institutional investors' bond demand in response to monetary policy is pivotal for firms' financing conditions, our work is closely related to Fabiani, Heineken, and Falasconi (2022). The authors reveal that a monetary loosening lengthens corporate debt maturity. In addition, Grosse-Rueschkamp, Steffen, and Streitz (2019) highlight that asset purchase programs of central banks induce firms to substitute loans with bonds, stimulating banks' risk-taking in corporate credit. We contribute to this literature by combining insights from these two papers and highlighting the influence of monetary policy on loan markets through institutional investors' bond demand.

Lastly, there is a burgeoning literature about the implications of monetary policy on shifts of lending volumes from the banking to the shadow banking sector (Chen, Ren, and Zha, 2018; Nelson, Pinter, and Theodoridis, 2018; Elliott, Meisenzahl, Peydró, et al., 2022; Sarto and Wang, 2022; Elliott, Meisenzahl, and Peydro, 2023). Our results cater to two important groups of nonbanks, insurers, and mutual funds, which affect the banking sector through lending in corporate bond markets.

3.2 Data

For our analysis, we build two different panel data sets to analyze the heterogeneous response of mutual funds and insurers to monetary policy and identify spillover effects on the syndicated loan market. We connect various data sources on corporate bonds, insurers' and mutual funds' portfolio holdings, syndicated loans, and firms' characteristics to do so. This section describes our data sources and summarizes key variables and statistics of our sample. We explain the exact panel structure in the relevant sections.

3.2.1 Data Description

Corporate bonds. We get information on corporate bond issues from the Mergent Fixed Income Security Database (FISD). To define our sample of corporate bond bonds, we closely follow Ma, Streitz, and Tourre (2023). We collect information on the issuance amount, offering and maturity date, seniority, and embedded call options. We complement this information with historical ratings from DUFF and Phelps Rating, Fitch, Moody's, and Standard & Poor's. If multiple ratings are available, we use the best rating and always consider the latest one. For further details on the sample selection and the data construction, see Appendix 3.A.1.

Portfolio holdings of institutional investors. Our analysis considers two types of institutional investors: insurers and mutual funds. We retrieve end-of-quarter security-level holdings of U.S. open-ended mutual funds from the Center for Research in Security Prices (CRSP) Survivorship Bias-Free Mutual Fund Portfolio Holdings database to track mutual funds' bond holdings. Some mutual funds report their quarterly bond holdings at the end of a month, which does not coincide with the end of a quarter. For consistency, we keep only end-of-quarter bond holdings of mutual funds. From 2008 to 2020, the total par value of bond holdings reported at the end of a quarter accounts for more than 88 percent of the total par value of bond holdings, which comprise the latest within-quarter report. For our final sample, however, we only consider the period between 2010 Q3 and 2019

Q2 because of irregularities in the data in 2010 Q1 that would affect our analysis. For a more detailed discussion of the data irregularities, see Appendix 3.A.2.

Insurance companies in the U.S. must report detailed financial statements to the National Association of Insurance Commissioners (NAIC), mainly for supervisory and regulatory purposes. We obtain security-level end-of-year corporate bond holdings of U.S. life and property and casualty (P&C) insurance companies from Schedule D Part 1 of the statutory filings. Combining the end-of-year holdings with transaction-level data on bond acquisitions and disposals from Schedule D Part 3, 4, and 5 allows us to track insurers' bond holdings at the end of every quarter between 2008 Q1 and 2019 Q2 (see, e.g., Ge and Weisbach (2021)). However, we consider only the period between 2010 Q3 and 2019 Q2 in our analysis due to the data irregularities in the mutual funds data in 2010 Q1.

We restrict our sample to insurers' and mutual funds' bond holdings between the offering date and the maturity date reported in Mergent FISD. In our analysis, we measure all bond holdings using par values to focus solely on changes in quantities and exclude revaluation effects due to changes in market prices or accounting standards.

Syndicated loans. We retrieve data on the syndicated corporate loan market from Thomson Reuters LoanConnector DealScan. In a syndicated loan, multiple lenders give a loan to a single borrower.[2] A syndicated loan typically consists of several tranches that vary in credit conditions, such as maturity or loan type. The lenders can be either banks or nonbanks. Each syndicate has at least one lead arranger. This lead arranger is in charge of the communication with the borrower and, in the book-building process, markets the different loan tranches to other lenders, i.e., the other participants in the syndicate (Elliott, Meisenzahl, and Peydro, 2023). We do not aim to curtail the demand-driven reaction of borrowers due to changes in bond market activity. Hence, we restrict our analysis to lead arranger lenders, as their lending amount results from demand and supply. In contrast, the lending amount of syndicate participants allocated in the book-building process is beyond the borrower's control. Moreover, we drop amended tranches because they do not necessarily entail new credit (Roberts, 2015). We also drop a few observations with lead arrangers, which we classify as insurance companies, to alleviate concerns that insurers acting as bond investors and creditors in syndicated loans might bias our results.[3] Apart from a few exceptions, DealScan provides only information on tranche amounts but not lender-specific loan amounts. We impute

2. Syndicated loans are the main loan-based financing tool for large corporations in the U.S. In the late 2010s, quarterly issuance on syndicated loan markets was even larger than quarterly issuance of corporate bonds (see stlouisfed.org).

3. To obtain information on the institution type of the lender, we use the variable "InstitutionType" in the Company DealScan Legacy data set. If the variable is missing, we manually classify insurance companies based on whether the company name contains the word "insurance"

missing lender shares using a similar procedure as in Chodorow-Reich (2014b), based on average shares of lead arrangers and syndicate participants. Eventually, we collapse our loan data to the borrower-lender-time level, which involves average maturities of loans weighted by their imputed amount.[4]

Firms' characteristics. We obtain quarterly data on firms' balance sheets and income statements via CRSP Compustat Merged (CCM). We use this data to control for firms' characteristics in our analysis. We always use the latest available information of a firm within a quarter. As is standard procedure, we drop financials (SIC Codes 6,000 - 6,999) and utilities (SIC codes 4,900 - 4,999). Furthermore, CCM is part of our historical matching procedure of bond issuers and borrowers of syndicated loans, which we describe in detail in Appendix 3.A.3. The GVKey of each firm, appearing as a bond issuer or borrower in a syndicated loan, serves as our relevant firm identifier over time.

Macroeconomic variables. Lastly, we supplement our data with information on macroeconomic variables from FRED, such as GDP, inflation, central bank asset purchases, and treasury yields. Moreover, we use the quarterly excess bond premium from Favara, Gilchrist, Lewis, and Zakrajsek (2016) to control for changes in the bond premium. Lastly, we add high-frequency changes in 10-year U.S. Treasury yields from Bauer and Swanson (2023) and the orthogonalized monetary policy shocks from Bauer and Swanson (2023).

3.2.2 Sample Description

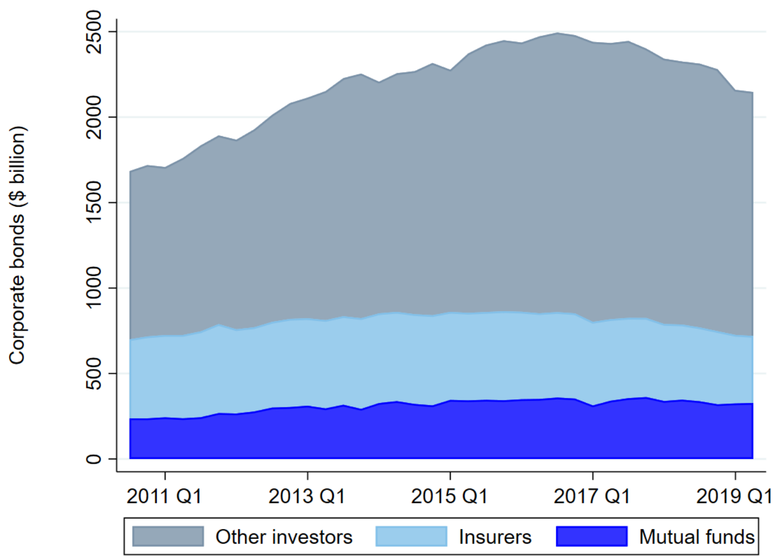
Our final sample comprises 1,065 publicly traded nonfinancial firms between 2010 Q3 and 2019 Q2. These firms had a positive amount of outstanding bonds and took out at least one syndicated loan during our sample period, i.e., they have manifestly access to both financing instruments. Furthermore, we aggregate corporate bond holdings of 3,261 U.S. insurance companies and 3,071 U.S. mutual funds (see Table 3.C.1). In Figure 3.2.1, we decompose the outstanding amount of a subset (due to our data limitations of outstanding bond amounts) of our considered bonds into three investor groups, which are holding these bonds: U.S. insurers, U.S. mutual funds, and other investors including foreign investors. Conditional on positive bond holdings of insurers or mutual funds, the share of outstanding bonds held by the two investor types fluctuates between 30 and 45 percent over time, making them the largest corporate bond investors (Koijen and Yogo, 2023). Therefore, they have a considerable impact on bond prices and are the focus of our

or "assurance". The link between lender identifiers in DealScan Legacy and lender identifiers in DealScan LoanConnector is established via the corresponding linking table in WRDS.

4. While we identify borrowers via their matched GVKey (see Appendix 3.A.3), we keep lender identifiers from DealScan.

analysis. Corporate bond financing has substantially increased since the financial crisis and accounted for more than double the amount allocated to loan financing (term loans and undrawn credit lines) within the debt structure of U.S. publicly listed firms over the last decade (Berg, Fabisik, and Sautner, 2021).

Figure 3.2.1. Corporate bond holdings of investors



Notes: This figure shows the aggregate investor composition of corporate bonds in our sample from 2010 Q3 to 2019 Q2. We proxy for other investors' holdings with the difference between the total outstanding amount and the par values held by insurers and mutual funds. We restrict the sample to bond-year-quarter observations with available information on outstanding amounts and positive bond holdings of either insurers or mutual funds. For further information on the sample selection, see Appendix 3.A.1.

For our analysis of spillover effects on the loan market, we exploit loan issuances of 477 lenders. To identify the monetary transmission to the loan market through bond market activity, we require firms to simultaneously have positive amounts of outstanding bonds held by insurers or mutual funds and at least one syndicated loan taken out. For this reason, our sample of borrowers drops to 791 nonfinancial firms.[5] Table 3.2.1 summarizes the distribution of our main variables. Using a similar classification as in Elliott, Meisenzahl, and Peydro (2023), we estimate that about 60 percent of our lenders are banks, and the remaining lenders are nonbanks. The probability of a firm taking out a loan in a quarter is 9 percent, implying firms frequently negotiate new loans. The average loan in our sample amounts to more than $ 1 billion with a maturity of 4.46 years. Therefore, the

5. We use the word "firm" in the framework of investors' demand for firms' bonds and frequently the word "borrower" when we address spillovers to the loan market. Both terms refer to the same unit of analysis.

average maturity of loans is considerably lower than that of firms' bonds, which is more than 13 years.

Table 3.2.1. Summary statistics

	N	Mean	SD	1st	25th	Median	75th	99th
Firm variables (firm-time level)								
1(New loan)	24,757	0.09	0.28	0.00	0.00	0.00	0.00	1.00
Rating	24,469	11.63	4.78	3.00	8.00	11.00	14.00	25.00
Assets ($ bn)	24,628	18.43	44.89	0.36	2.42	5.82	15.02	224.61
Sales ($ bn)	24,672	3.51	8.55	0.04	0.44	1.07	2.88	37.99
Cash ($ bn)	24,628	1.30	4.17	0.00	0.08	0.31	0.99	15.38
Leverage	24,618	0.69	0.26	0.27	0.53	0.64	0.79	1.59
Long-term debt	24,614	0.36	0.22	0.01	0.21	0.32	0.46	1.06

	N	Mean	SD	1st	25th	Median	75th	99th
Loan variables								
Amount ($ mn)	2,626	1,015.50	2,109.01	13.50	97.46	256.65	868.18	11,380.58
Loan maturity	2,604	4.46	1.97	1.00	3.21	4.87	5.01	10.01
1(Bank)	2,621	0.60	0.49	0.00	0.00	1.00	1.00	1.00

	N	Mean	SD	1st	25th	Median	75th	99th
Bond variables								
Issuance amount ($ mn)	13,854	531.34	635.86	0.17	200.00	375.00	695.10	3,000.00
Maturity at issuance	13,854	13.13	10.68	2.25	7.02	10.01	15.01	40.05
1(Callable)	12,326	0.97	0.16	0.00	1.00	1.00	1.00	1.00

	N	Mean	SD	1st	25th	Median	75th	99th
Macroeconomic variables								
10-yr T-Yield (%)	36	2.38	0.47	1.62	2.01	2.33	2.76	3.41
ΔGDP (%)	36	2.36	0.68	0.94	1.80	2.28	2.89	3.97
ΔPCE (%)	36	1.51	0.68	0.14	1.22	1.52	1.85	2.96
EBP (pp)	36	-0.06	0.24	-0.36	-0.19	-0.12	-0.00	0.81

Notes: **Firm-time variables. 1**(*New loan*) is an indicator variable equal to 1 if a borrower took out at least one tranche of a syndicated loan granted by at least one lead arranger in a quarter. *Rating* refers to the rounded median rating of all bonds outstanding by a firm at the end of a quarter. The rating of a bond refers to the rating at the end of a quarter, i.e., the latest available rating of the bond from DUFF and Phelps Rating (DPR), Fitch Rating (FR), Moody's Rating (MR) and Standard and Poor's Rating (SPR) within the quarter. Ratings are converted to integers from 1 to 23, AAA to D, and NR, respectively. If multiple ratings are available at the same rating date, we use the best, i.e., lowest, rating. *Assets* are a firm's total assets in USD at the end of a quarter. *Sales* is a firm's quarterly sales in USD. *Cash* is a firm's cash holdings in USD at the end of a quarter. *Leverage* is a firm's total leverage divided by total assets at the end of a quarter. *Long-term debt* is a firm's fraction of debt with maturity above one year.
Lender-time variables. *Amount* represents the loan amount that is granted by a lender within a quarter using a similar imputing procedure as in Chodorow-Reich (2014b). *Loan maturity* is the average maturity in years weighted by the corresponding loan amounts of all loans a lender grants within a quarter. **1**(*Bank*) is an indicator variable that takes the value 1 if the lender is a bank following the classification of Elliott, Meisenzahl, and Peydro (2023).

Table 3.2.1 continued.

Bond-level variables. *Issuance amount* is a bond's offering amount. *Maturity at issuance* is a bond's maturity at the offering date in years. **1**(*Callable*) is an indicator variable that takes the value 1 if a bond is callable.
Macroeconomic variables. *10-year T-Note* is the end-of-quarter market yield on U.S. Treasury securities at 10-year constant maturity. *ΔGDP* is the annualized growth of the U.S. gross domestic product. *ΔPCE* is the annualized inflation in the U.S. Personal Consumption Expenditures price (PCE) index. *EBP* is the quarterly excess bond premium by Favara, Gilchrist, Lewis, and Zakrajsek (2016).

3.3 Investors' Bond Demand in Response to Monetary Policy

This section investigates differences in insurers' and mutual funds' corporate bond demand in response to monetary policy. Exploiting the granularity of our data, which enables us to disentangle investors' demand and firms' supply of corporate bonds, we find that a contractionary interest rate change caused by monetary policy decreases mutual funds' bond holdings stronger than insurers' bond holdings. The effect is particularly pronounced among high-yield and bonds of medium maturity.

Insurance companies and mutual funds combine for a significant fraction of U.S. corporate bond holdings (see Figure 3.2.1). However, these two investor groups substantially differ in their liability structure. Mutual funds allow investors to redeem their funds anytime, creating the risk of quick outflows upon interest rate changes. In contrast, insurers have stable liabilities as their outflows depend on variables unrelated to financial markets, e.g., disaster damages, or their products contain clauses that make redemption of funds unattractive, e.g., surrender options (Kubitza, Grochola, and Gründl, 2023). These facts suggest that insurers and mutual funds react differently to interest rate changes as documented on an aggregate level by Fang (2023).

To examine these differences empirically, we construct a security-investor-time panel that tracks investors' aggregate bond holdings at the security level over time. More specifically, our panel shows for investor type j, being either insurers or mutual funds (in the aggregate), the holdings of security s at the end of quarter t. For the panel, we aggregate bond holdings of single insurers and mutual funds' portfolios to security-specific end-of-quarter holdings at the investor level. We manually fill in zero bond holdings for investor type j when our data sources do not report holdings for this investor in time t, i.e., no insurer (mutual fund) had security s in its corporate bond portfolio at the end of quarter t.

Using this panel, we examine the relationship between investors' bond demand and monetary policy by estimating the regression specification,

$$\begin{aligned} \text{Log}(1 + \text{Bonds})_{j,s,t} = {} & \beta \; \mathbf{1}(\text{Mutual funds}_j) \times \text{10-yr T-Yield}_t \\ & + \gamma \boldsymbol{X} + u_{s,t} + v_{j,s,year} + w_{j,s,season} + \varepsilon_{j,s,t}, \end{aligned} \tag{3.3.1}$$

where the dependent variable, $Log(1 + \text{Bonds})_{j,s,t}$ is the natural logarithm of 1 plus the par value held by investor j in security s at the end of quarter t. $\mathbf{1}(\textit{Mutual funds}_j)$ is an indicator variable that takes the value 1 if investor j represents the aggregate mutual fund sector. $\textit{10-yr T-Yield}_t$ is the 10-year U.S. Treasury yield at the end of quarter t. $\boldsymbol{X}$ is a vector of controls including interactions of $\mathbf{1}(\textit{Mutual funds}_j)$ with bond characteristics, i.e., the bond's *Rating* and *Maturity*, as well as several lagged macroeconomic variables, i.e., ΔGDP, ΔCPI, and *EBP*. $u_{s,t}$, $v_{j,s,year}$, and $w_{j,s,season}$ are security-time, investor-security-year, and investor-security-season fixed effects, where "season" denotes the four quarters of a year. We cluster standard errors at the investor-firm level to account for error term correlations within an investor-firm pair across time.

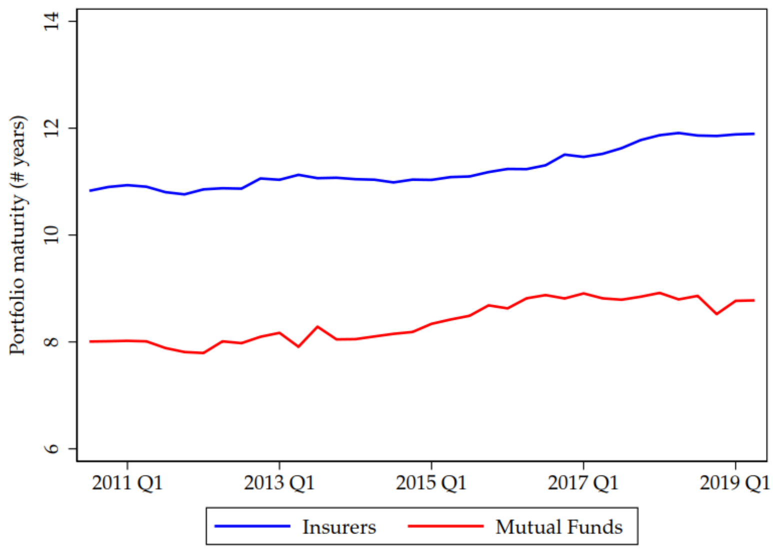
Our main coefficient of interest is β, which gives us the differential response of mutual funds' bond demand relative to insurers in response to changes in market yields. The structure of our panel allows us to identify this differential demand response cleanly. More specifically, we can apply the approach from Khwaja and Mian (2008) and include security-time fixed effects, $u_{s,t}$, which control for any supply-driven changes in investors' holdings. In other words, with the security-time fixed effects, our identifying variation stems exclusively from variation in ownership within an outstanding bond in response to monetary policy. Additionally, investor-security-year fixed effects, $v_{j,s,year}$, and investor-security-season fixed effects, $w_{j,s,season}$, absorb investor-specific yearly and seasonal components in bond holdings.[6]

To tackle endogeneity issues in the 10-year U.S. Treasury yield, we apply an instrumental variables approach and use the cumulative sum of all high-frequency changes in the 10-year U.S. Treasury yield in a 30-minute window around FOMC meetings from Bauer and Swanson (2023) as instrument for the current 10-year U.S. Treasury yield. Pioneered by Gürkaynak, Sack, and Swanson (2005), high-frequency changes are nowadays the main tool to measure monetary policy shocks. In the regressions, following Elliott, Meisenzahl, Peydró, et al. (2022), we use the cumulative sum of these changes to proxy for the stance of monetary policy. In contrast to other papers that exploit monetary policy shocks based on high-frequency changes in short-term yields, we use high-frequency surprises in 10-year U.S. Treasury yields. We choose this approach for several reasons. First, the maturity structure of insurers and mutual funds suggests measuring shocks to longer maturity yields. The business model of insurers and mutual funds makes them typically long-term investors. For example, insurers' underwriting business

6. Natural disasters have a strong seasonal pattern and induce both mutual funds (Tubaldi, 2020) and insurers (Ge and Weisbach, 2021; Liu, Rossi, and Yun, 2021; Massa and Zhang, 2021; Kubitza, 2023) to sell assets. Kamstra, Kramer, Levi, and Wermers (2017) document that mutual funds are additionally exposed to seasonality in investors' risk aversion. Moreover, regulatory changes can lead to asset reallocations of investors in specific years (Becker, Opp, and Saidi, 2022).

equips them with stable liabilities (Chodorow-Reich, Ghent, and Haddad, 2021). They use the proceeds to earn investment income (Knox and Sørensen, 2024). At the same time, mutual funds are a vehicle to accumulate capital for retirement savings. Figure 3.3.1 confirms this notion and shows that the portfolio maturity of both insurers and mutual funds is close to 10 years, with mutual funds slightly lower (around 8 years) than insurers (around 11 years). Hence, changes in the 10-year U.S. Treasury yield should better reflect these investors' exposure to monetary policy.

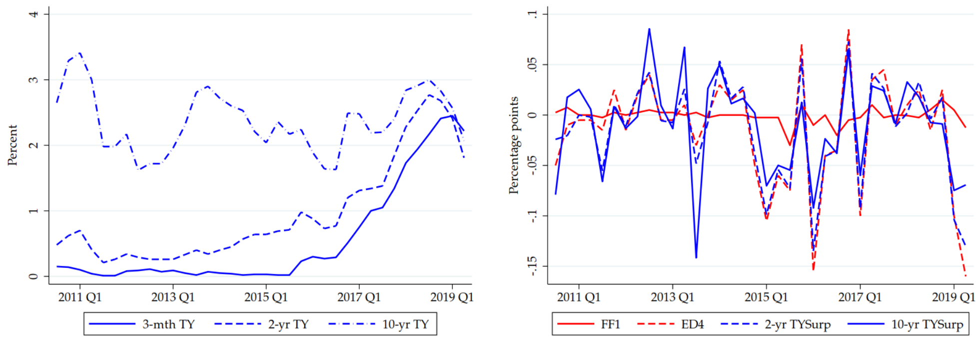
Figure 3.3.1. Portfolio maturity of investors



Notes: This figure shows the average portfolio maturity of insurers and mutual funds between 2010 Q3 and 2019 Q2. The average is weighted by the par value of the security held by the investor type in aggregate.

Second, the 10-year Treasury yield was not constrained by the ZLB period, which spans a significant part of our sample period. In 2009 Q1, the Federal Funds rate reached the ZLB and remained nearly zero until 2015 Q3. The Fed made enormous asset purchases to drive down long-term interest rates in the following. During this period, short-term interest rates did move little, while the ZLB did not constrain long-term rates (see panel (a) of Figure 3.3.2). Panel (b) of Figure 3.3.2 shows that the ZLB also impacted the high-frequency changes in asset prices. The figure suggests that the ZLB did not constrain the high-frequency changes in the 2-year and 10-year U.S. Treasury yields. However, high-frequency changes in the current-month Federal Funds future (FF1) and the three-quarter ahead Eurodollar future (ED4) - two asset prices used frequently for identifying monetary policy shocks (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Swanson, 2021; Bauer and Swanson, 2023) - were much more minor during the ZLB period than after the ZLB period. The FF1 moved only slightly around FOMC meetings in the ZLB period and showed more substantial changes after the ZLB period. The ED4 moved substantially less than the 10-year U.S. Treasury market yield during the ZLB period. Still, it moved closely after the ZLB period. For this reason, we use the high-frequency changes in the 10-year U.S. Treasury yield. In robustness checks, we use the monetary policy shocks of Bauer and Swanson (2023) to show that our results are robust.

Figure 3.3.2. Monetary policy, the ZLB period, and market yields



(a) Market yields

(b) High-frequency changes

Notes: This figure shows (a) the time series of market yields of U.S. Treasury notes of different maturities, and (b) the sum of all high-frequency changes of current-month federal funds futures (FF1), three-quarter ahead eurodollar futures, and market yields of U.S. Treasury notes of different maturities within a quarter. All time series show the sample period from 2010 Q3 to 2019 Q2.

Table 3.3.1 shows the results of equation 3.3.1. In column (1), we estimate the equation with ordinary least squares. The estimate shows that an increase in the 10-year U.S. Treasury yield decreases mutual funds' corporate bond demand relative to insurance companies, but the coefficient is insignificant. In columns (2) to (5), we instrument the 10-year U.S. Treasury yield with the monetary policy stance. Applying the IV approach, we find that an increase in the 10-year U.S. Treasury yield leads to a significantly stronger decrease in bond demand for mutual funds than for insurers (columns (2) and (3)). As our dependent variable, Log(1+Bonds), combines both extensive and intensive margin, we dissect these in columns (4) and (5). In column (4), we estimate equation 3.3.1 with an indicator variable $\mathbf{1}(\text{Bonds}_{j,s,t})$ that takes the value 1 if investor j has bond s in its aggregate investor portfolio at the end of quarter t. The results show no significant difference in the extensive margin, i.e., mutual funds' lower corporate bond demand is not driven by mutual funds unwinding entire positions. In column (5), we take $\text{Log}(\text{Bonds})_{j,s,t}$, the natural logarithm of the par value of security s held by investor j at the end of quarter t, as the dependent variable and focus only on bonds in which insurers and mutual funds actually invest. Here, we find that mutual funds react significantly more strongly. The coefficient is highly significant and negative, implying that mutual funds scale down on existing holdings stronger than insurers. These findings align with previous literature on insurers' and mutual funds' investment behavior in response to aggregate shocks (Fang, 2023; Kubitza, 2023).

In Table 3.C.2, we examine the robustness of our result. In column (1), we use the shocks from Bauer and Swanson (2023) as an instrument for the 10-year U.S. Treasury yield. These shocks are based on changes in short-term yields, i.e., those constrained during the ZLB period, and are orthogonalized to macroeconomic information. [7] The coefficient on the interaction term is again negative and highly significant. In column (2), we run the IV regression from 2010 Q3 to 2015 Q3, i.e., the part of our sample period overlapping with the ZLB period. The results remain unchanged, although the difference in responses is lower. In column (3), we use a matching procedure before the IV regression to keep only bonds for which there is an appropriate match. More specifically, we build buckets based on a bond's rating, maturity, quarter, and three-digit SIC industry of the issuer. We keep only bonds for which there is at least one bond in the same bucket. In the IV regression, we then include investor-rating-maturity-industry fixed effects. The coefficient remains negative and highly significant. In columns (4) to (9), we repeat the robustness checks for the extensive and intensive margin. In all cases, the direction of the coefficients stays unchanged, and the intensive margin is statistically highly significant. These results suggest that mutual funds adjust their demand for corporate bonds strongly in response to a monetary shock compared to insurance companies. In particular, the reduction in existing holdings drives this differential reaction.

In the following, we inspect how insurers and mutual funds react differently to monetary policy. More specifically, we investigate whether different maturities or bond rating preferences drive the differential response. First, to inspect differences regarding maturities, we separately estimate regression 3.3.1 for the subsample of short-term bonds, i.e., bonds with a remaining maturity lower than 3 years, mid-term bonds, i.e., a remaining maturity between 3 and 10 years, and long-term bonds, i.e., a remaining maturity of more than 10 years. Table 3.C.3 shows the results for the separate regressions. We find no differences between insurers and mutual funds among the short-term and long-term bonds. However, an increase in market yields reduces mutual funds' demand stronger than for the mid-term

7. Bauer and Swanson (2023) suggest this approach to account for the predictability of monetary policy shocks with macroeconomic information. They argue that this predictability stems from the Fed reacting to macroeconomic information and market participants consequently learning about the Fed's monetary policy rule. This argument contrasts the literature on the "Fed information effect", which claims that the Fed transmits information about the state of the economy to investors (Romer and Romer, 2000; Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2021).

bonds. Dissecting the extensive and intensive margin, we find that the intensive margin drives the differential reaction.

Table 3.3.1. Investors' demand for bonds in response to monetary policy

	Dependent variable				
	$Log(1 + Bonds)_{j,s,t}$			Extensive margin	Intensive Margin
	(1)	(2)	(3)	(4)	(5)
$\mathbf{1}(\text{Mutual funds}_j) \times$ 10-yr T-Yield$_t$	-0.070 [0.05]	-0.751** [0.38]	-0.761** [0.38]	-0.013 [0.02]	-0.680*** [0.11]
Investor × Macro controls	Yes	Yes	Yes	Yes	Yes
Security-Time FE	Yes	Yes	Yes	Yes	Yes
Investor-Security-Year FE	Yes	Yes	Yes	Yes	Yes
Investor-Security-Season FE	Yes	Yes	Yes	Yes	Yes
Investor-Maturity FE			Yes	Yes	Yes
Investor-Rating FE			Yes	Yes	Yes
Estimation	OLS	IV	IV	IV	IV
Instrument	Level 10-yr T-Yield Surp$_t$				
Kleibergen-Paap rk Wald F stat.		354	340	340	209
No. of obs.	311,142	311,142	296,346	296,346	236,424

Notes: This table shows estimates for the relationship between interest rates and institutional investors' investment behavior, i.e., equation 3.3.1. In columns (1) to (3), the dependent variable $Log(1 + Bonds)_{j,s,t}$ is the natural logarithm of 1 plus the par value held by investor *j* in security *s* at the end of quarter *t*. In column (4), the dependent variable $\mathbf{1}(Bonds_{j,s,t})$ is an indicator variable that takes the value of one if investor *j* holds any positive amount of bond *s* at the end of quarter *t*, i.e., the extensive margin. In column (5), the dependent variable $Log(Bonds)_{j,s,t}$ is the natural logarithm of the par value of bond *s* held by investor *j* at the end of quarter *t*, i.e., the intensive margin. *10-yr T-Yield*$_t$ denotes the 10-year U.S. Treasury yield at the end of quarter *t*. $\mathbf{1}(\textit{Mutual funds}_j)$ is an indicator variable that takes the value of 1 if investor *j* represents the aggregate investments of mutual funds. We instrument *10-yr T-yield*$_t$ with *Level 10-yr T-Yield Surp*$_t$, the cumulative sum of all high-frequency changes in the 10-year U.S. Treasury yield around FOMC meetings from Bauer and Swanson (2023) until quarter *t*. We control for bond characteristics and bond supply with security-time fixed effects. Additionally, we control for investors' preferences by including investor-maturity and investor-rating fixed effects. A security's maturity is the remaining maturity of bond *s* at the end of quarter *t* clustered into the following buckets: 0-1 years, 1-3 years, 3-5 years, 5-10 years, 10-15 years, 15-20 years, and greater than 20 years. We control for several lagged macro variables, *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the investor-firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Second, we examine differences regarding credit ratings. To do so, we separately run regression 3.3.1 for the subsample of investment-grade and high-yield bonds (see Table 3.C.4). We find that an increase in the 10-year U.S. Treasury yield reduces mutual funds' corporate bond demand more strongly for high-yield bonds, while there is no effect for investment-grade bonds. Consistent with the previous findings, the intensive margin drives the results, i.e., mutual funds scaling down more on portfolio bonds. In the intensive margin, mutual funds also scale down stronger on portfolio investment-grade bonds. However, the extensive margin masks this effect because mutual funds' probability of holding a bond in their portfolio increases relative to insurers. This result aligns with mutual funds investing in high-yield bonds to reach for yield (Choi and Kronlund, 2018). As the interest rates rise, high-yield bonds become less attractive, and mutual funds sell them to satisfy redemptions or reallocate the funds to safer bonds.

Our results suggest that mutual funds' bond demand reacts more strongly to a monetary-policy-induced yield change than insurance companies' bond demand. Even though we do not take a stance on the source of these differential responses to yield changes, they are ostensibly consequences of different regulation or liability structures, including customer behavior (Becker and Ivashina, 2015; Chodorow-Reich, Ghent, and Haddad, 2021; Coppola, 2022). For example, due to minimum return guarantees in life insurance contracts, policyholders tend to retain their annuities, which affects the bond investment behavior of life insurers (Ozdagli and Wang, 2019).

3.4 Spillovers to the Loan Market

In this section, we identify spillovers of corporate bond demand to the syndicated loan market. Based on our results in the previous section, we build a variable combining pre-shift firm-specific exposure to insurers with aggregate bond demand changes of insurers and mutual funds. We document that changes in investor composition induced by monetary policy significantly impact firms' decisions to take up loans. These results are robust to various specifications and are stronger for firms with a medium-maturity bond structure and high-yield firms.

3.4.1 Baseline Results

The changes in end-of-quarter bond holdings of investors capture both acquisitions of newly issued bonds and acquisitions and disposals in the secondary bond market. The literature documents the general impact of demand shifts on asset prices (Koijen, Richmond, and Yogo, 2019; Jansen, 2023) and a strong linkage between the activity of institutional investors in the secondary bond market and financing and investment decisions of nonfinancial firms (Coppola, 2022; Siani, 2022; Kubitza, 2023). Building on our results in the previous section, we focus on demand shifts triggered by monetary policy. To do so, we use a lender-borrower-time panel that tracks the borrowing relationships of the firms whose bonds we examined in the previous section. More specifically, our panel shows whether a borrower-lender pair negotiated at least one new loan in a quarter and, if so, the average amount and characteristics of the newly granted loans. For all periods in which a borrower-lender did not negotiate a new loan, i.e., most periods for the average lender-borrower pair, we set the loan amount and the indicator variable for a new loan to zero.

To identify the spillovers of corporate bond demand on firms' loan demand, we use a regression specification of the following form,

$$\text{Loan outcome}_{b,l,t+1} \;=\; \beta \; \Delta\text{Bond demand}_{b,t} + \boldsymbol{\gamma X} + u_{l,t} + \varepsilon_{b,l,t+1}, \qquad (3.4.1)$$

Essentially, equation 3.4.1 estimates how changes in the demand for borrower b's bonds in a quarter t influence the credit relationship between lender l and borrower b in the next period $t+1$ where outcomes can be, e.g., the decision to take out a new loan or the size of new loans.

However, estimating this effect faces several challenges. First, the spillover effects on the loan market can be rooted in firms' reaction to bond market activity (induced by monetary policy) or lenders' immediate response to monetary policy changes.[8] We want to separate these channels and rule out that changes in the lender's credit supply drive the changes in the loan outcome. To do so, we exploit the fact that lenders typically have multiple borrowers in our panel, and, hence, we can use the Khwaja and Mian (2008) approach and include lender-time fixed effects, $u_{l,t}$, which absorb any borrower-invariant changes in credit supply.[9] In this case, our results are driven by differential changes in bond demand across borrowers and reflect spillover effects triggered via two potential channels. On the one hand, nonfinancial firms might incorporate current conditions in the bond market in their financing decision and adjust their loan demand accordingly. On the other hand, financial institutions that provide syndicated loans to nonfinancial firms might closely monitor the bond market, e.g., because they simultaneously offer credit to the firm and underwriting services or serve as dealers in the firms' bond transactions.[10] These financial institutions might reconsider their loan supply because they compete with bond investors to provide credit. For example, consider a specific firm facing improved financing conditions in the bond market thanks to heightened demand for its outstanding bonds. In response, banks may improve contractual loan terms or reduce markups on loan offers for this firm, aiming to retain the firm as its customer.

The second challenge is to measure the changes in bond demand. Accounting measures like the change in outstanding bonds would be erroneous as these are

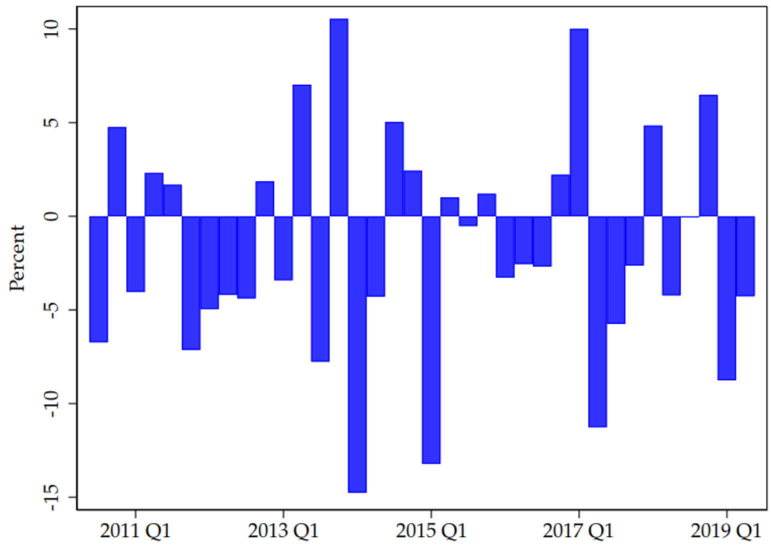
8. The literature discusses various transmission mechanisms of monetary policy that have an immediate impact on banks, e.g., bank reserves, balance sheet revaluation, risk appetite of banks, market power in deposit markets, or structural differences between banks and nonbanks (Bernanke and Blinder, 1992; Jiménez et al., 2012; Dell'Ariccia, Laeven, and Suarez, 2017; Drechsler, Savov, and Schnabl, 2017; Rodnyansky and Darmouni, 2017; Chakraborty, Goldstein, and MacKinlay, 2020; Elliott, Meisenzahl, Peydró, et al., 2022).

9. Note that this does not rule out that the lender differentially changes its credit supply across borrowers, i.e., tailoring credit supply to the specific borrower. For example, Ippolito, Peydró, Polo, and Sette (2016) show that lenders tailor credit supply to borrowers.

10. Neuhann and Saidi (2018) show that universal banks' ability to use the information generated in different business sections benefits firms as the banks can make more educated credit decisions which stimulate firm productivity.

equilibrium outcomes that solely result from supply and demand changes. To circumvent this problem, we measure changes in the demand for firms' bonds using an approach similar to a shift-share variable. The variable we construct comprises two components: an aggregate shock variable and a firm's exposure to the shock. The results of the previous section motivate both of these variables.

Figure 3.4.1. Variation in $g_I - g_{MF}$ over time



Notes: This figure shows the quarterly difference in growth rates of insurers' and mutual funds' corporate bond holdings, i.e., $g_I - g_{MF}$, over the sample period from 2010 Q3 to 2019 Q2.

First, we define the shock variable,

$$g_{I,t} - g_{MF,t} = \frac{\Delta \text{Par value}_{I,t}}{\text{Par value}_{I,t-1}} - \frac{\Delta \text{Par value}_{MF,t}}{\text{Par value}_{MF,t-1}}, \tag{3.4.2}$$

where *Par value*$_{I,t}$ (*Par value*$_{MF,t}$) is the par value held by insurers (mutual funds) at the end of quarter t, and *ΔPar value*$_{I,t}$ (*ΔPar value*$_{MF,t}$) is the change in par value held by insurers (mutual funds) from quarter $t-1$ to t. Put differently, $g_{I,t} - g_{MF,t}$ measures the difference in the growth rate of the investment portfolios of insurers and mutual funds, i.e., the relative change in bond demand of insurers and mutual funds. The results in the previous section suggest that monetary policy directly affects this variable, which refers to differential demand changes between insurers and mutual funds over time. In contrast to unconditional aggregate holdings shifts that can result from either changes in bond demand or bond supply, the difference in growth rates of bond holdings of insurers and mutual funds captures changes in bond investors' engagement. Hence, this variable is a more suitable proxy for changes in bond demand. To construct this variable, we aggregate our investor-bond-level data to the investor level and then calculate the growth rates of the par value of bonds held by insurers and mutual funds for each quarter. Figure 3.4.1 shows the time series of $g_{I,t} - g_{MF,t}$. The variable substantially varies over time, aligning with the documented differences in bond demand sensitivity. As mutual funds are more sensitive, these primarily drive the difference in growth rates. Table 3.C.5 shows that the growth rate in mutual funds' holdings explains most of the variation in the difference in growth rates.

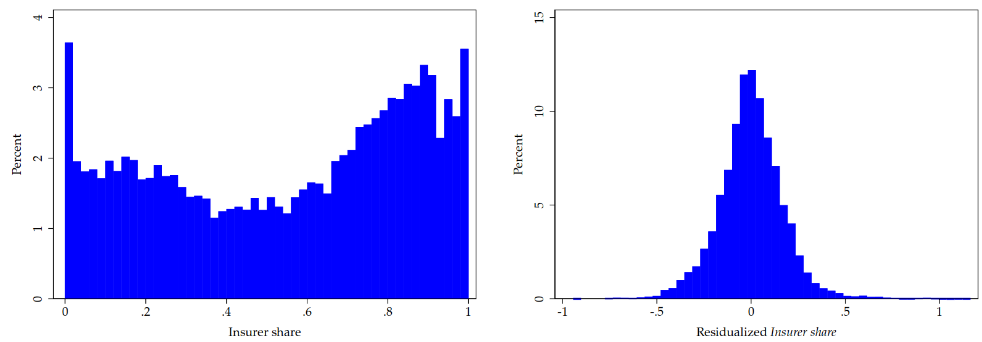
Second, we define the firm's exposure to the aggregate shock as the investor composition of mutual funds and insurers,

$$\text{Insurer share}_{b,t-1} = \frac{\text{Bonds held by insurers}_{b,t-1}}{\text{Bonds held by insurers and mutual funds}_{b,t-1}}, \tag{3.4.3}$$

where *Bonds held by insurers*$_{b,t-1}$ is the par value of bonds of borrower b held by insurance companies at the end of quarter $t-1$, and *Bonds held by insurers and mutual funds*$_{b,t-1}$ is the par value of bonds of borrower b held by insurers and mutual funds at the end of quarter $t-1$. To calculate these variables, we consider all bonds that were part of our analysis in the previous section and aggregate the respective par values. In turn, we consider in our analysis only firms where insurers and mutual funds combined held a positive amount of outstanding bonds. The results in the previous section suggest that the *Insurer shrare* is a relevant proxy for a firm's exposure to aggregate demand changes. As mutual funds react more sensitively, a shock to aggregate demand induced by monetary policy should differentially affect firms depending on their initial investor composition. Panel (a) of Figure 3.4.2 shows the distribution of the variable *Insurer share*. There are many firm-time pairs where either insurers or mutual funds are nonexistent; overall, they make up only around 7 percent of all observations. In between these two extremes, the importance of insurers relative to mutual funds is dispersed, with insurers being the more important investor group in the majority of cases, i.e., the distribution is slightly right-skewed because insurers are overall the larger investor group than mutual funds. To address the potential concern that the investor composition is endogenous to firm characteristics, panel (b) of Figure 3.4.2 shows the residuals of a regression of the insurer share on firm characteristics, ratings and 4-digit SIC-industry fixed effects. The figure suggests that firm characteristics can explain a part of the variation in investor composition but do not explain all variation in the insurer share as the distribution remains dispersed. There are several reasons for the remaining variation in the insurer share. First, on the investor side, both mutual funds (Fang, 2023) - unless they track a broad index - and insurers (Kubitza, 2023) maintain a narrow investment universe. Both investor types typically scale up the holdings of their existing portfolio rather than dedicating funds to new firms. Second, on the firm side, firms normally maintain few underwriter relationships, and these underwriters, in turn, have a limited number of investors in their network. As

Fang (2023) argues, if these bond underwriters tend to have more of one type of investor, the firm will naturally have a larger share of either insurers or mutual funds.

Figure 3.4.2. Firm-level importance of insurers relative to mutual funds



(a) Raw distribution **(b)** Residuals

Notes: This figure shows (a) the pooled distribution of the variable *Insurer share* and (b) the pooled distribution of the residuals from a regression of *Insurer share* on firms' fundamentals. The variable *Insurer share* is the par value of a firm's corporate bonds held by insurers divided by the sum of the par value of a firm's corporate bonds held by insurers and mutual funds. In panel (b), we plot the residuals from a regression of *Insurer share* on firms' *Log(Assets)*, *Log(Sales)*, *Log(Cash)*, *Leverage*, *Long-term debt*, and median borrower *Rating*.

Together, the interaction term of the shock and exposure variables captures our variation in changes to firm-specific bond demand.[11] Suppose, for example, that the difference in growth rates between insurers and mutual funds is positive, i.e., aggregate insurer holdings either grew more than mutual funds' holdings or decreased by less. Suppose further that the share of firm b's bonds held by insurers compared to mutual funds is large. This firm should experience a higher demand for their bonds relative to firms with a lower share of insurers on their investor basis.

Finally, we control in equation 3.4.1 for firm-specific supply changes, which are not a response of lenders to bond market activity. We include borrowers' balance sheet information, i.e., *Log(Cash)*, *Log(Sales)*, *Log(Assets)*, *Leverage*, and *Long-term debt*, and the median *Rating* of the borrower's outstanding bonds in our regression to absorb any of these changes. We also control the Fed's quantitative easing (QE) efforts. QE programs heterogeneously affect firms across firm size

11. Note that we can rewrite the interaction term as follows,

$$\text{Insurer share}_{b,t-1} \times (g_{I,t} - g_{MF,t}) = \text{Insurer share}_{b,t-1} \times g_{I,t} + (\text{Mutual fund share})_{b,t-1} \times g_{MF,t} - g_{MF,t}. \tag{3.4.4}$$

Apart from the last term, which is absorbed by time fixed effects, this expression decomposes the growth of outstanding bonds of borrower b held by the two bond investors into an investor-borrower-specific "share" and an aggregate investor-type "shift", which resembles the structure and underlying idea of a Bartik instrument more closely.

or riskiness, which might bias our estimates (Bittner, Rodnyansky, Saidi, and Timmer, 2023). Hence, in our most stringent specifications, we interact the borrower characteristics with a metric for the asset purchases of the Federal Reserve.

In our first test, we estimate the extensive margin of loan market outcomes, i.e.,

$$\begin{aligned}\mathbf{1}(\text{New loan}_{b,l,t+1}) \;=\; & \alpha \text{ Insurer share}_{b,t-1} + \beta \text{ Insurer share}_{b,t-1} \\ & \times \;(\mathrm{g}_{I,t} - \mathrm{g}_{MF,t}) + \gamma \boldsymbol{X}_{b,t-1} + u_{l,t} + v_{b,l} + \varepsilon_{b,l,t+1},\end{aligned} \tag{3.4.5}$$

where $\mathbf{1}(\textit{New loan}_{b,l,t+1})$ is an indicator variable that takes the value 1 if borrower b takes out a new loan from lender l in quarter t. $\textit{Insurer share}_{b,t-1}$ and $(g_{I,t} - g_{MF,t})$ are the exposure and shock variables as defined above. $\boldsymbol{X}$ is a vector of controls containing the firm-level variables (interacted with the Fed's QE efforts) defined above and several macroeconomic variables, i.e., *ΔGDP*, *ΔCPI*, and *EBP*. Additionally, we include firm fundamentals. $u_{l,t}$ and $v_{b,l}$ are lender-time and borrower-lender fixed effects, respectively. We cluster standard errors at the borrower level. As we want to shed light on bond demand conditional on monetary policy changes and the indirect monetary transmission to loan market outcomes, we instrument $(g_{I,t} - g_{MF,t})$ with the sum of all high-frequency changes in the 10-year U.S. Treasury market yield within quarter t.

Table 3.4.1 reports the results of our IV estimates of equation 3.4.5. The Kleibergen and Paap (2006) F statistics are in all specifications well above 10. Hence, our instrument satisfies the relevance condition (as implied by the first step). We obtain negative estimates for the coefficient of the interaction term, which are statistically significant in all specifications. A firm experiencing higher demand for its bonds than others in response to a monetary policy shock is relatively less likely to take out a loan within the subsequent quarter. This effect is robust to various sets of controls and fixed effects.

The effect is also economically sizable. For example, consider a scenario where monetary policy induces a difference in bond portfolio growth rates between insurers and mutual funds of 2 percentage points, approximately corresponding to the third quartile of the distribution of the variable. A firm whose share of insurers on the investor basis is one standard deviation higher, i.e., by 33 percentage points, compared to another firm, has a probability of taking out a loan that is about 0.8 percentage points lower than the probability of taking out a loan of the other firm. As the likelihood of taking out a loan in a quarter is around 9 percent, this effect is economically meaningful.

Table 3.4.1. Spillover of bond demand change on loan market conditional on monetary policy

	Dependent variable: $\mathbf{1}(\text{New loan}_{b,l,t+1})$				
	(1)	(2)	(3)	(4)	(5)
Insurer share$_{b,t-1}$ × ($g_{I,t} - g_{MF,t}$)	-1.257***	-1.287**	-1.428***	-1.421**	-3.826**
	[0.48]	[0.51]	[0.54]	[0.62]	[1.70]
Insurer share$_{b,t-1}$	-0.010	-0.040*	-0.107***	-0.121***	-0.120**
	[0.02]	[0.02]	[0.04]	[0.04]	[0.05]
Lender-Time FE	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes
Borrower-Year FE	Yes	Yes	Yes	Yes	Yes
Borrower-Season FE	Yes	Yes	Yes	Yes	Yes
SIC3-Time FE				Yes	Yes
Borrower controls		Yes	Yes	Yes	Yes
Borrower rating		Yes	Yes	Yes	Yes
Macro controls × Insurer share			Yes	Yes	Yes
Borrower controls × QE			Yes	Yes	Yes
Borrower rating × QE			Yes	Yes	Yes
Borrower controls × ($g_I - g_{MF}$)					Yes
Borrower rating × ($g_I - g_{MF}$)					Yes
Estimation	IV	IV	IV	IV	IV
Instrument	10-yr T-Yield Surp$_t$				
Kleibergen-Paap rk Wald F stat.	379	329	278	140	43
No. of obs.	223,398	218,209	218,209	218,091	218,091

Notes: This table estimates the relationship between changes in investors' corporate bond demand and firms' loan demand. The dependent variable, $\mathbf{1}(\textit{New loan}_{b,l,t+1})$, is an indicator variable that takes the value of 1 if at least one syndicated loan is granted by lender l to borrower b within quarter $t+1$. *Insurer share*$_{b,t-1}$ is the share of firm b's bonds held by insurers out of the total amount of bonds held by insurers and mutual funds at the end of quarter $t-1$. The independent variable ($g_{I,t} - g_{MF,t}$) is the difference in the growth rates of insurers' and mutual funds' corporate bond holdings in nonfinancial institutions in quarter t. We instrument ($g_{I,t} - g_{MF,t}$) with *10-yr T-Yield Surp*$_t$, the sum of all high-frequency changes in the 10-year U.S. Treasury market yield over quarter t. We control for several lagged borrower characteristics, i.e., *Log(Assets)*, *Log(Sales)*, *Log(Cash)*, *Leverage* and *Long-term debt*, the lagged median borrower *Rating*, and macroeconomic conditions, i.e., *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the borrower level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.4.2 Robustness Checks and Drivers

To assess whether our results are robust, we first repeat the IV estimation of equation 3.4.5, instrumenting the difference in growth rates with a different shock series. In column (1) of Table Table 3.4.2, we use the monetary policy shocks of Bauer and Swanson (2023) instead of the high-frequency changes in the 10-year U.S. Treasury yield. We find that the main coefficient of interest stays negative and highly significant. In column (2), we assess whether the spillovers are robust to the ZLB period, using only the part of the sample period that overlaps with the ZLB period. Again, our results remain qualitatively unchanged.

Table 3.4.2. Robustness of spillover effects

	Dependent variable				
	$\mathbf{1}$(New loan$_{b,l,t+1}$)		Log(1+Loan)$_{b,l,t+1}$		
Specification:	Other MP shock	ZLB period			
	(1)	(2)	(3)	(4)	(5)
Insurer share$_{b,t-1}$ × $(g_{I,t} - g_{MF,t})$	-0.382***	-1.302***	-36.395***	-27.417***	-73.079**
	[0.15]	[0.12]	[11.99]	[10.19]	[31.98]
Insurer share$_{b,t-1}$	-0.092***	-0.312***	-2.015***	-2.037***	-2.318**
	[0.02]	[0.03]	[0.73]	[0.70]	[0.98]
Lender-Time FE	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes
Borrower-Year FE	Yes	Yes	Yes	Yes	Yes
Borrower-Season FE	Yes	Yes	Yes	Yes	Yes
SIC3-Time FE					Yes
Macro controls × Insurer share	Yes	Yes		Yes	Yes
Borrower controls	Yes	Yes		Yes	Yes
Borrower rating	Yes	Yes		Yes	Yes
Borrower controls × QE	Yes	Yes		Yes	Yes
Borrower rating × QE	Yes	Yes		Yes	Yes
Borrower controls × $(g_I - g_{MF})$					Yes
Borrower rating × $(g_I - g_{MF})$					Yes
Estimation	IV	IV	IV	IV	IV
Instrument	MPS_t^{orth}		10-yr T-Yield Surp$_t$		
Kleibergen-Paap rk Wald F stat.	10,400	21,642	230	278	43
No. of obs.	218,209	129,625	223,398	218,209	218,091

Notes: This table provides robustness checks for the relationship between changes in investors' corporate bond demand and firms' loan demand. In columns (1) to (3), the dependent variable, $\mathbf{1}$(*New loan*$_{b,l,t+1}$), is an indicator variable that takes the value of 1 if at least one syndicated loan is granted by lender l to borrower b within quarter $t+1$. In columns (4) to (6), the dependent variable *Log(1+Loan)*$_{b,l,t+1}$ is the natural logarithm of 1 plus the loan amount granted by lender l to borrower b in quarter $t+1$. *Insurer share*$_{b,t-1}$ is the share of firm b's bonds held by insurers out of the total amount of bonds held by insurers and mutual funds at the end of quarter $t-1$. The independent variable $(g_{I,t} - g_{MF,t})$ is the difference in the growth rates of insurers' and mutual funds' corporate bond holdings in nonfinancial institutions in quarter t. In columns (1), we instrument $(g_{I,t} - g_{MF,t})$ with MPS_t^{orth}, the sum of all monetary policy shocks identified by Bauer and Swanson (2023) over quarter t. In columns (2) to (5), we instrument $(g_{I,t} - g_{MF,t})$ with *10-yr T-Yield Surp*$_t$, the sum of all high-frequency changes in the 10-year U.S. Treasury market yield over quarter t. We control for several lagged borrower characteristics, i.e., *Log(Assets)*, *Log(Sales)*, *Log(Cash)*, *Leverage* and *Long-term debt*, the lagged median borrower *Rating*, and macroeconomic conditions, i.e., *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the borrower level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Next, we examine whether differential changes in bond demand also affect the intensive margin of loan market outcomes. To do so, we change the dependent variable in our IV approach for equation 3.4.5 with *Log(1+Loan)*$_{b,l,t+1}$, i.e., the natural logarithm of 1 plus the loan amount negotiated between borrower b and lender l in period $t+1$. Columns (3) to (5) of Table 3.4.2 show that the coefficient of the interaction term is again negative and significant in all specifications. Hence, the effect of bond demand on loan market outcomes is driven by the decision to take out a loan and the loan amount. Again, the effect is economically sizable. For the above-considered scenario with a difference in bond portfolio growth rates between insurers and mutual funds of 2 percentage points and a firm whose share of insurers on the investor basis is one standard deviation higher (33 percentage points), the loan amount taken up in a quarter is about 24 percent lower than the loan amount of the other firm, considering the coefficient in column (3).

In a further robustness check, we alternate the definition of our main independent variable. To further address concerns that investors might pre-select into certain firms, we modify our firm-specific exposure measure and consider the exposure of borrower b's industry peers to insurance company investors instead. More specifically, we define for each borrower b the *Industry insurer share*$_{-b,t-1}$, which is the share of bonds held by insurers in the 4-digit SIC industry of borrower b excluding borrower b of the total amount of bonds held by insurers and mutual funds in the 4-digit industry of borrower b excluding borrower b. As above, we calculate this variable for each borrower b at the end of quarter $t-1$. Interacting this measure with the difference in growth rates of bonds held by insurers and mutual funds, we capture the degree to which the borrower's industry is exposed to a differential aggregate demand shock. As we specifically exclude borrower b from the calculation of the industry exposure, we avoid any endogeneity concerns. An underlying assumption is that industry-wide shocks to bond demand also affect the bond demand of borrower b. This assumption seems reasonable as the literature documents firms' dependence on industry peers regarding financing decisions (MacKay and Phillips, 2005; Carvalho, 2015).

Table 3.4.3 presents the results of the IV estimation of equation 3.4.5 using a firm's industry peer exposure to insurers. Columns (1) and (2) show that the results stay quantitatively unchanged. If a firm's industry experiences higher relative bond demand, the firm is less likely to negotiate a new loan. This effect is, as before, robust to a variety of fixed effects and controls. In columns (3) and (4), we examine the intensive margin using the industry peers' exposure to insurers. As before, the estimates are negative and significant. Overall, our results are not driven by insurers pre-selecting certain firms.

Next, we want to understand the margin of adjustments of firms' lower loan take-up if they experience greater demand for their corporate bonds. To do so, we estimate our IV setup from equation 3.4.5 for several subsamples and other dependent variables. Specifically, we first analyze whether the type of lender matters for the loan take-up, i.e., a nonbank (excluding insurance companies) or a bank. Therefore, columns (1) and (2) of Table 3.4.4 report the results of equation 3.4.5

for the subsample of lender-borrower pairs with nonbank lenders or bank lenders. The results are qualitatively and quantitatively similar for both types of lenders. Firms with a higher relative bond demand significantly reduce their demand for loans from both nonbanks and banks. Second, we examine whether firms reduce their demand for particular types of loans, e.g., credit lines or term loans. Differences in the effects can be informative about the potential mechanism as credit lines serve liquidity management (Sufi, 2009) whereas term loans finance longer-term investments. In columns (3) to (5) of Table 3.4.4, we change the dependent variable of equation 3.4.5 to indicator variables whether the firm takes up a new credit line, a new term loan or any other loan. We classify loan types using the tranche type given in DealScan. We find that the demand for credit lines and term loans is lower for firms with higher relative bond demand. Only demand for other types of loans is unchanged, but as these encompass a variety of financing arrangements and make up for only a tiny fraction of the loans (see Figure 3.B.1), this result is not informative of the underlying mechanism. In Table 3.C.6, we also check for differences regarding relationship lenders, i.e., those with which the borrower previously had a loan relationship in the sample period and new lenders. There is no substantial difference between the two types.

Lastly, we focus on heterogeneities in the effect across borrowers' bond debt characteristics. The results in the previous section show that investors' differential bond demand changes concentrate on bonds with a maturity between 3 to 10 years and are particularly pronounced for high-yield bonds. We examine whether differences in the maturity or the credit quality of the borrower's outstanding bonds drive the effect of bond demand on loan market outcomes. Therefore, we split in Table 3.4.5 our sample across the average maturity of the borrower's outstanding bonds and the median rating of the borrower's outstanding bonds. In columns (1) to (3), we report the results of an IV estimation of equation 3.4.5 for three subsamples of firms, i.e., firms with an average maturity of bonds less than 3 years, an average maturity of between 3 and 10 years, and an average maturity of more than 10 years. For firms with a short remaining bond maturity, column (1) shows that the coefficient on the interaction term is positive but insignificant. Hence, there is no difference across relative bond demand for firms that must issue new bonds soon. Column (3) shows that the coefficient is negative but insignificant for firms with a long-dated bond maturity. Hence, there is again no difference in loan take-up. However, column (2) shows that the coefficient is negative and highly significant for firms with a medium bond maturity. Put differently, firms with a medium bond maturity are more likely to reduce their loan take-up if they experience higher relative bond demand. This finding aligns with the results in the previous section, as investors' bond demand changed for bonds with a medium maturity. Hence, firms with a medium bond maturity are more likely to be affected by bond demand changes that affect their loan demand. In columns (4) and (5), we split the sample across the median rating of the borrower's outstanding bonds. Analogous to before, we find that the effect is negative and significant only for high-yield bonds, i.e., those bonds that showed the strongest change in mutual funds' bond demand relative to insurers for changes in Treasury yields.

Table 3.4.3. Industry peers' bond demand changes and spillovers to firms' loan demand

	Dependent variable			
	$\mathbf{1}$(New loan$_{b,l,t+1}$)		Log(1+Loan)$_{b,l,t+1}$	
	(1)	(2)	(3)	(4)
Industry insurer share$_{-b,t-1}$ × ($g_{I,t} - g_{MF,t}$)	-1.895**	-1.903**	-34.957**	-35.167**
	[0.78]	[0.78]	[14.50]	[14.49]
Industry insurer share$_{-b,t-1}$	-0.182***	-0.182***	-3.421***	-3.417***
	[0.07]	[0.07]	[1.26]	[1.26]
Lender-Time FE	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes
Borrower-Year FE	Yes	Yes	Yes	Yes
Borrower-Season FE	Yes	Yes	Yes	Yes
SIC3-Industry-Time FE	Yes	Yes	Yes	Yes
Macro controls × Insurer share	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes
Borrower rating		Yes		Yes
Borrower controls × QE		Yes		Yes
Borrower rating × QE		Yes		Yes
Estimation	IV	IV	IV	IV
Instrument	10-yr T-Yield Surp$_t$			
Kleibergen-Paap rk Wald F stat.	117	118	117	118
No. of obs.	425,115	425,115	425,115	425,115

Notes: This table estimates the relationship between changes in investors' industry-specific corporate bond demand and firms' loan demand across the industry's exposure to demand changes. In columns (1) to (3), the dependent variable, $\mathbf{1}$(*New loan*$_{b,l,t+1}$), is an indicator variable that takes the value of 1 if at least one syndicated loan is granted by lender l to borrower b within quarter $t+1$. In columns (4) to (6), the dependent variable *Log(1+Loan)*$_{b,l,t+1}$ is the natural logarithm of 1 plus the loan amount granted by lender l to borrower b in quarter $t+1$. *Industry insurer share*$_{b,t-1}$ is the share of the industry's bonds (excluding borrower b) held by insurers out of the total amount of the industry's bonds (excluding borrower b) held by insurers and mutual funds at the end of quarter $t-1$. The independent variable ($g_{I,t} - g_{MF,t}$) is the difference in the growth rates of insurers' and mutual funds' corporate bond holdings of nonfinancial institutions in quarter t. We instrument ($g_{I,t} - g_{MF,t}$) with *10-yr T-Yield Surp*$_t$, the sum of all high-frequency changes in the 10-year U.S. Treasury market yield over quarter t. We control for several lagged borrower characteristics, i.e., *Log(Assets)*, *Log(Sales)*, *Log(Cash)*, *Leverage* and *Long-term debt*, the lagged median borrower *Rating*, and macroeconomic conditions, i.e., *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the borrower level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Overall, these empirical tests show, first, that the effect of bond demand on loan market outcomes is robust to various specifications and, second, that there seems to be a substitution effect at play. Our results align with previous findings in Grosse-Rueschkamp, Steffen, and Streitz (2019), which document that the ECB's QE program led to firms substituting bank loans for bond financing. However, in contrast to Grosse-Rueschkamp, Steffen, and Streitz (2019), the substitution is not driven by the direct effect of monetary policy relaxing firms' credit constraints but by the differential bond demand changes of insurers and mutual funds. Hence, we interpret our findings as evidence that investor composition determines how monetary policy transmits to firms.

Table 3.4.4. Drivers of the spillovers

	Dependent variable: $\mathbf{1}(\text{New loan}_{b,l,t+1})$				
Lender subsample/Type of loan:	Nonbank	Bank	Credit line	Term loan	Other loan
	(1)	(2)	(3)	(4)	(5)
Insurer share$_{b,t-1}$ × ($g_{I,t} - g_{MF,t}$)	-1.688**	-1.306**	-1.014**	-0.779**	-0.103
	[0.77]	[0.54]	[0.47]	[0.38]	[0.16]
Insurer share$_{b,t-1}$	-0.088*	-0.114***	-0.109***	-0.043	-0.007
	[0.05]	[0.04]	[0.03]	[0.03]	[0.01]
Lender-Time FE	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes
Borrower-Year FE	Yes	Yes	Yes	Yes	Yes
Borrower-Season FE	Yes	Yes	Yes	Yes	Yes
Macro controls × Insurer share	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
Borrower rating	Yes	Yes	Yes	Yes	Yes
Borrower controls × QE	Yes	Yes	Yes	Yes	Yes
Borrower rating × QE	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV
Instrument	10-yr T-Yield Surp$_t$				
Kleibergen-Paap rk Wald F stat.	161	286	278	278	278
No. of obs.	67,073	150,970	218,209	218,209	218,209

Notes: This table analyzes the drivers of the relationship between changes in investors' corporate bond demand and firms' loan demand. The dependent variable, $\mathbf{1}(\textit{New loan}_{b,l,t+1})$, is an indicator variable that takes the value of 1 if at least one syndicated loan is granted by lender l to borrower b within quarter $t+1$. *Insurer share*$_{b,t-1}$ is the share of firm b's bonds held by insurers out of the total amount of bonds held by insurers and mutual funds at the end of quarter $t-1$. The independent variable $(g_{I,t} - g_{MF,t})$ is the difference in the growth rates of insurers' and mutual funds' corporate bond holdings in nonfinancial institutions in quarter t. We instrument $(g_{I,t} - g_{MF,t})$ with *10-yr T-Yield Surp*$_t$, the sum of all high-frequency changes in the 10-year U.S. Treasury market yield over quarter t. We control for several lagged borrower characteristics, i.e., *Log(Assets)*, *Log(Sales)*, *Log(Cash)*, *Leverage* and *Long-term debt*, the lagged median borrower *Rating*, and macroeconomic conditions, i.e., *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the borrower level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.4.5. Heterogeneity of spillovers across bond maturity structure and credit ratings

	Dependent variable: $\mathbf{1}(\text{New loan}_{b,l,t+1})$				
Maturity/Credit rating:	Short-term	Mid-term	Long-term	Investment grade	High yield
	(1)	(2)	(3)	(4)	(5)
Insurer share$_{b,t-1}$ × ($g_{I,t}$ − $g_{MF,t}$)	4.037	-1.551***	-1.186	-0.849	-4.813***
	[3.82]	[0.60]	[1.41]	[1.52]	[1.42]
Insurer share$_{b,t-1}$	-0.650	-0.072	-0.353***	-0.154**	-0.145*
	[0.39]	[0.05]	[0.12]	[0.07]	[0.09]
Lender-Time FE	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes
Borrower-Year FE	Yes	Yes	Yes	Yes	Yes
Borrower-Season FE	Yes	Yes	Yes	Yes	Yes
Macro controls × Insurer share	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes
Borrower rating	Yes	Yes	Yes	Yes	Yes
Borrower controls × QE	Yes	Yes	Yes	Yes	Yes
Borrower rating × QE	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV
Instrument	10-yr T-Yield Surp$_t$				
Kleibergen-Paap rk Wald F stat.	6	193	37	14	46
No. of obs.	6,154	144,839	53,371	129,148	84,254

Notes: This table analyzes the drivers of the relationship between changes in investors' corporate bond demand and firms' loan demand. The dependent variable, $\mathbf{1}(\textit{New loan}_{b,l,t+1})$, is an indicator variable that takes the value of 1 if at least one syndicated loan is granted by lender l to borrower b within quarter $t+1$. *Insurer share*$_{b,t-1}$ is the share of firm b's bonds held by insurers out of the total amount of bonds held by insurers and mutual funds at the end of quarter $t-1$. The independent variable ($g_{I,t} - g_{MF,t}$) is the difference in the growth rates of insurers' and mutual funds' corporate bond holdings in nonfinancial institutions in quarter t. We instrument ($g_{I,t} - g_{MF,t}$) with *10-yr T-Yield Surp*$_t$, the sum of all high-frequency changes in the 10-year U.S. Treasury market yield over quarter t. We control for several lagged borrower characteristics, i.e., *Log(Assets)*, *Log(Sales)*, *Log(Cash)*, *Leverage* and *Long-term debt*, the lagged median borrower *Rating*, and macroeconomic conditions, i.e., *ΔGDP*, *ΔPCE*, and the *EBP* by Favara (2016). We cluster standard errors at the borrower level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

3.5 Conclusion

This paper investigates the spillovers from monetary policy-induced changes in corporate bond demand on firms' demand for syndicated loans. We follow a two-step procedure to establish a link between institutional investors' changes in bond demand following monetary policy surprises and firms' borrowing relationships. First, we show that a monetary-policy-induced increase in interest rates induces insurers and mutual funds to adjust their corporate bond demand but to different degrees. Hence, firms experience differential changes in the demand for their bond debt. Next, we exploit these findings to examine the impact on firms' credit relationships. Constructing a shift-share-like variable that builds on the results in the first step, we show that firms with a relatively higher demand for their bonds are less likely to take up a loan following a contractionary shock.

Previous work delineates monetary policy transmission channels to lending outcomes that apply directly to the creditors' balance sheet or the bond market. Our findings emphasize the role of institutional investors in that setting. We derive evidence that their different sensitivities in bond demand heterogeneously affect firms due to their investor base. Eventually, this leads to relative differences in the likelihood of taking out new loans among firms, drawing meaningful conclusions for the conduct of monetary policy.

Our findings address interdependencies of financial markets due to firms' choice between different debt instruments. Even though we provide the first evidence on the mechanism behind the spillover effects, future research may seek to analyze further the characteristics of new loans taken out to disclose potential implications for the structure of corporate debt or the pricing of loans. In turn, this can lead to natural effects, e.g., in terms of investment decisions. While our empirical identification relies on differential demand effects, the magnitude of how our results translate into aggregate effects remains to be shown in future work, whose main challenge is identifying these effects.

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Appendix 3.A Sample Construction and Variable Definitions

3.A.1 Sample Selection of Corporate Bonds

Apart from a few exceptions, we closely follow Ma, Streitz, and Tourre (2023) in our sample selection of corporate bonds from the Mergent FISD Bond Issues dataset. More specifically, we apply the following steps.

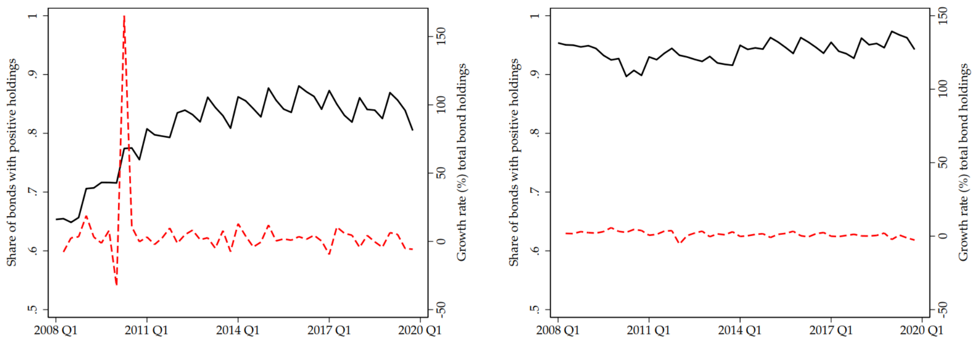
1. We restrict the sample to corporate bonds of the following type: Corporate Debentures ("CDEB"), Corporate Medium Term Notes ("CMTN"), Corporate Pass Through Trusts ("CPAS"), Retail Notes ("RNT"), and Corporate Payment-in-Kind Bonds ("CPIK").
2. We keep non-preferred, non-convertible, non-exchangeable, non-puttable bonds and bonds with fixed coupons.
3. We keep U.S. dollar-denominated bonds of issuers whose country of domicile or country of permanent residence is the U.S.
4. We drop bonds issued by financial firms (SIC codes 6,000 - 6,999) and utility firms (SIC codes 4,900 - 4,999).
5. To merge bond issuance data from Mergent FISD to CRSP Mutual Fund Portfolio Holdings in a later stage, we add the 8-digit CUSIP of each bond based on the 9-digit CUSIP in the Mergent FISD database. Since there are a few bonds with different 9-digit CUSIPs but the same 8-digit CUSIP, we keep only the bond with the latest offering date among bonds with the same 8-digit CUSIP.
6. We drop bonds with missing information on the bond's offering or maturity date. We then restrict the sample period to bonds with maturity dates after 2007 Q4 and offering dates before 2019 Q3.
7. We keep only those bond-issuing firms that we manage to merge to data of syndicated loans from LoanConnector DealScan (see Section 3.A.3 for the linking procedure from bond issuers to borrowers of syndicated loans).

The Bond Issues dataset provides further information on bond characteristics, such as offering date, maturity date, or seniority. Moreover, we add information on embedded call options of issued bonds from the Mergent FISD Bond Redemption dataset. We build the history of ratings of outstanding bonds both at the CUSIP-year-quarter and GVKey-year-quarter level based on the Mergent FISD Bond Ratings dataset. More specifically, we adjust DUFF and Phelps Rating (DPR), Fitch Rating (FR), and Moody's Rating (MR) to the scale of Standard and Poor's Rating (SPR). We take the best rating if there are multiple bond ratings at a given date. We then keep the latest available rating of each bond within each quarter and construct the history of end-of-quarter bond ratings by selecting the latest available rating over time. Among all outstanding bonds of a firm at the end of a quarter, we take the median rating to obtain the history of ratings at the GVKey-year-quarter level. We retrieve information on the history of bonds' outstanding amounts from the "fisd_amt_out_hist" table. We do not observe outstanding amounts of every bond in our sample. Still, we use the data to gauge the size of bond holdings of insurers and mutual funds out of outstanding bonds (see Figure 3.2.1).

3.A.2 Irregularities in the Mutual Funds Data

After the cleaning steps described above, we note that the mutual funds' data from CRSP Mutual Fund Portfolio Holdings contains irregularities in 2010 Q1. More specifically, aggregate mutual fundings inferred from CRSP decreased by more than 30 percent from 2009 Q4 to 2010 Q1 to then more than double from 2010 Q1 to 2010 Q2 (see panel (a) of Figure 3.A.1). Moreover, the share of bonds in our sample that appear in the aggregate mutual fund portfolio stays virtually the same from 2009 Q4 to 2010 Q1 but then makes a jump from 2010 Q1 to 2010 Q2. We assume that this pattern is an irregularity as a similar pattern cannot be observed for insurance companies (see panel (b) of Figure 3.A.1). Here, the share of bonds that appear in insurers' aggregate portfolio and the growth rate of aggregate holdings is much more steady.

Figure 3.A.1. Tracking quality of insurers and mutual funds

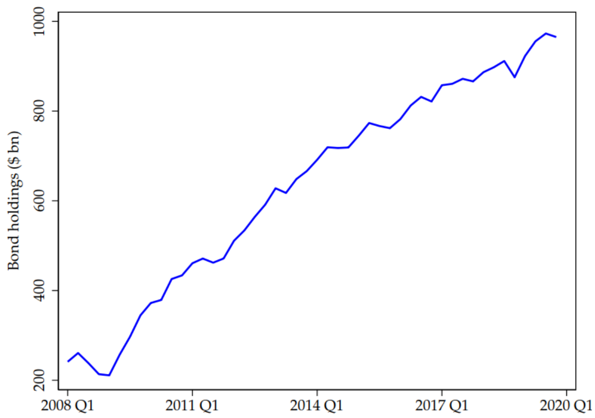


(a) Mutual funds **(b)** Insurers

Notes: This figure shows the quality of our portfolio tracking for insurers and mutual funds. Panel (a) shows the share of bonds that appear in the aggregate portfolio of mutual funds (black line) and the growth rate of mutual funds' aggregate holdings (red dashed line) over time. Panel (b) shows the share of bonds that appear in the aggregate portfolio of insurers (black line) and the growth rate of insurers' aggregate holdings (red dashed line) over time.

Looking at data on mutual funds' corporate bond holdings of nonfinancial corporations from FRED as another data source, we observe a steady increase over time (see Figure 3.A.2) and, in particular, no significant decline from 2009 Q4 to 2010 Q1 and subsequent increase from 2010 Q1 to 2010 Q2. Although the FRED data considers all corporate bonds in mutual funds' portfolios, whereas we filter bonds in the sample selection (see 3.2), the selection process is unlikely to drive the irregularity in the CRSP data.

Figure 3.A.2. Mutual funds' holdings of nonfinancial corporate bonds from FRED



Notes: This figure shows aggregate mutual funds' holdings of nonfinancial corporate bonds from the FRED database.

The documented irregularities could result from irregularities in the CRSP database's coverage. Schwarz and Potter (2016) document that the mutual funds' data became reliable only after 2008. After we applied the above-described cleaning steps with great caution, we could not explain the irregularity of the data in 2010 Q1. As our explanatory variable in the second part of the analysis depends on investors' aggregate bond holdings changes, we decide to start our sample only in 2010 Q3. This way, we ensure that the data is reliable. Moreover, we automatically exclude the period after the 2008 crisis from our sample, ensuring that firms' extraordinary behavior during the crisis cannot drive our results.

3.A.3 Linking Bond Issuers to Borrowers of Syndicated Loans

We establish the historical match between bond issuers of corporate bonds in Mergent FISD and borrower identifiers in LoanConnector DealScan in two main steps:

1. **Linking borrower identifiers in LoanConnector DealScan to GVKeys:** First, we exploit the corresponding linking table provided in WRDS to match tranche identifiers in LoanConnector DealScan to facility identifiers in DealScan Legacy. After that, we use the updated link of Chava and Roberts (2008) to assign each borrower of a particular issued tranche of a syndicated loan its corresponding "GVKey" at the time of issuance. The remaining duplicate observations regarding the LoanConnector DealScan tranche identifier "LPC_Tranche_ID" are evidently due to amended tranches. Therefore, we keep

only the observation among duplicates with the earliest "facilitystartdate", as merged from the Chava and Roberts (2008) linking table, i.e., the observation that pertains to the facility or tranche at origination.

2. **Linking issuers of outstanding bonds to GVKeys:** Our procedure is similar to the procedure by Ma, Streitz, and Tourre (2023). In the first step, we use the Bond CRSP Link Table from WRDS, which provides a dynamic link between CUSIP, the unique security identifier in Mergent FISD, and PERMCO, the unique identifier of a firm in CCM. Based on the start and end date of the link, we fill in end-of-quarter connections between CUSIP and PERMCO over the sample period. We drop a few CUSIP-year-quarter duplicates. In the second step, we leverage quarterly information from CCM to connect "PERMCO" identifiers with "GVKey" identifiers over time. Finally, we tackle the remaining missing historical links using the following approach:

    a. If we can establish at least one link for a given bond to the "GVKey" of the issuer at a given year-quarter, we fill in missing "GVKey" identifiers for remaining year-quarter observations of this bond with the latest available "GVKey". If there is no latest available "GVKey", we take the earliest available "GVKey".

    b. For missing "GVKey" identifiers, we leverage the variable "ISSUER_ID" in Mergent FISD. For every quarter, we look for bonds with linked "GVKey" identifiers assigned the same "ISSUER_ID" as the bond without "GVKey". If there is such a bond, we impute the corresponding "GVKey" for the issuer of the bond without "GVKey" at the considered quarter (if there are multiple bonds with linked identifiers, we arbitrarily take the numerically highest "GVKey"). We then go back to step 1. We repeat the same procedure by leveraging first the variable "AGENT_ID" and then the variable "PARENT_ID" in Mergent FISD.

    c. For remaining missing GVKeys, we leverage the variable "ISSUER_ID again " in Mergent FISD but without time restriction, i.e., we assign "GVKey" identifiers of linked bonds to bonds with missing identifiers if all these bonds have the same "ISSUER_ID" across the whole sample period (again, if there are multiple bonds with linked GVKeys and the same "ISSUER_ID", we arbitrarily take the numerically highest GVKey). We repeat the same procedure by leveraging first the variable "AGENT_ID" and then the variable "PARENT_ID" in Mergent FISD.

3.A.4 Variable Definitions

Table 3.A.1. Variable definitions and data sources

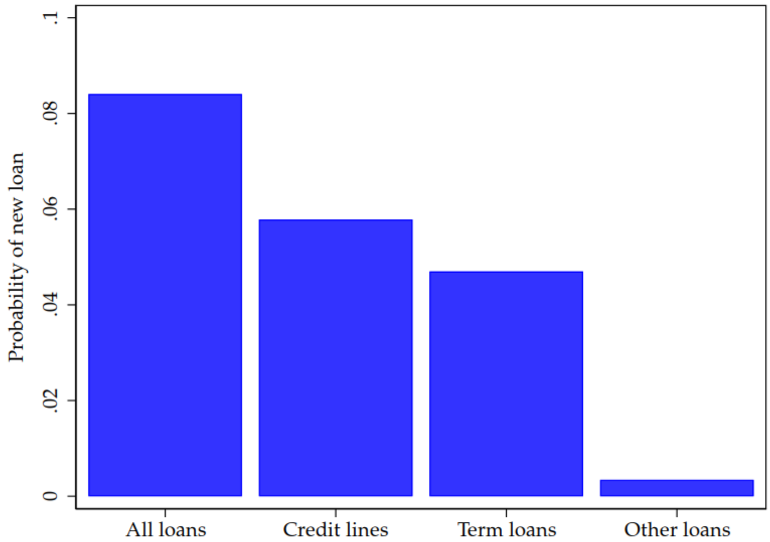
Variable	Definition (Unit)
	Firm-level variables
Bond rating	Rounded median rating of all bonds outstanding of a firm at the end of a quarter. We use the best rating if multiple ratings are available at the same time. *Source: Duff and Phelps, Fitch, Moody's, S&P.*
Assets	A firm's total assets at the end of a quarter. *Source: Compustat.*
Sales	A firm's quarterly total sales in USD. *Source: Compustat.*
Cash	A firm's cash holdings in USD at the end of a quarter. *Source: Compustat.*
Leverage	A firm's total liabilities divided by total assets at the end of a quarter. *Source: Compustat.*
Long-term debt	A firm's share of debt that has a maturity of less than one year at the end of a quarter. *Source: Compustat.*
Insurer share	Share of a firm's bonds held by insurers out of the total amount of bonds held by insurers and mutual funds at the end of a quarter. *Source: Own calculations.*
Industry insurer share	Share of an industry's bonds (excluding the firm's bonds) held by insurers out of the total amount of bonds held by insurers and mutual funds at the end of a quarter. *Source: Own calculation.*
	Investor-bond-level variables
Bonds	Total par value held of a bond by mutual funds or insurers at the end of a quarter. *Source: NAIC and CRSP.*
1(Mutual funds)	An indicator variable that takes the value 1 if the investor type represents insurers or mutual funds. *Source: NAIC and CRSP.*
Maturity	Remaining time between the end of a quarter and a bond's maturity date. *Source: Mergent FISD.*
Rating	Credit rating of a bond at the end of a quarter. If multiple credit ratings are available, we take the best rating. *Source: Mergent FISD.*
Issuance amount	A bond's offering amount at issuance. *Source: Mergent FISD.*
Maturity at issuance	A bond's maturity at issuance. *Source: Mergent FISD.*

Table 3.A.1 continued.

	Lender-borrower-level variables
1(New loan)	An indicator variable that takes the value 1 if a borrower-lender pair has negotiated at least one new loan within a quarter. *Source: LoanConnector DealScan.*
Loan amount	The loan amount newly borrowed by a firm from a lender in a quarter. *Source: LoanConnector DealScan.*
Loan maturity	The average maturity of the new syndicated loans borrowed by a firm from a lender in a quarter. *Source: LoanConnector DealScan.*
1(Bank)	An indicator variable that takes the value 1 if the lender is a bank institution.
	Macroeconomic variables
EBP	The excess bond premium. *Source: Favara, Gilchrist, Lewis, and Zakrajsek (2016).*
GDP growth	The annualized GDP growth rate. *Source: FRED.*
CPI inflation	The annualized CPI inflation rate. *Source: FRED.*
1(QE)	An indicator variable that takes the value 1 in periods when the Fed did quantitative easing. *Source: .*
10-yr T-Yield Surp	Sum of all high-frequency changes in the 10-year Treasury yield around FOMC meetings over a quarter. *Source: Bauer and Swanson (2023).*
Level 10-yr T-Yield Surp	Cumulative sum of all past high-frequency changes in the 10-year Treasury yield around FOMC meetings until the end of a quarter. *Source: Bauer and Swanson (2023).*
MPS^{orth}	Sum of all monetary policy shocks identified by Bauer and Swanson (2023) over a quarter. *Source: Bauer and Swanson (2023).*
Level MPS^{orth}	Cumulative sum of all monetary policy shocks identified by Bauer and Swanson (2023) until the end of quarter. *Source: Bauer and Swanson (2023).*
g_I	The quarterly growth rate of insurers' total bond holdings. *Source: CRSP.*
g_{MF}	The quarterly growth rate of mutual funds' total bond holdings. *Source: CRSP.*

Appendix 3.B Additional Figures

Figure 3.B.1. Probability of taking out a loan



Notes: This figure shows the probability of a firm taking out a loan in a quarter and the probability of a firm taking out a credit line, a term loan, or any other loan. We classify loan types using the tranche type given in DealScan.

Appendix 3.C Additional Tables

Table 3.C.1. Information on sample

Panel 1: Investor-bond-time analysis	
Number of insurers	3,261
Life insurers	816
P&C insurers	2,445
Number of mutual fund portfolios	3,071
Number of firms	1,065
Panel 2: Lender-borrower-time analysis	
Number of borrowers	791
Number of lenders	477
Number of borrower-lender pairs	5,905

Notes: This table contains additional information on (1) our investor-security-time panel to examine investors' corporate bond demand and (2) our lender-borrower-time panel to examine spillover effects of investors' bond demand on the syndicated loan market. Note that we aggregate insurers' and mutual funds' portfolios to the investor-type level. Moreover, note that firms in the first panel act as borrowers in the second panel.

Table 3.C.2. Robustness: Investors' demand for bonds in response to monetary policy

	Dependent variable								
	$\text{Log}(1+\text{Bonds})_{j,s,t}$			Extensive margin			Intensive margin		
Specification:	Other MP shock	ZLB period	Matching	Other MP shock	ZLB period	Matching	Other MP shock	ZLB period	Matching
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbf{1}(\text{Mutual funds}_j) \times$ 10-yr T-Yield$_t$	-1.631***	-0.378***	-1.299***	-0.059***	-0.018**	-0.051**	-0.831***	-0.150***	-0.841***
	[0.30]	[0.12]	[0.41]	[0.02]	[0.01]	[0.02]	[0.11]	[0.04]	[0.15]
Investor × Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Security-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Season FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Maturity FE	Yes	Yes		Yes	Yes		Yes	Yes	
Investor-Rating FE	Yes	Yes		Yes	Yes		Yes	Yes	
Investor-Rating-Maturity-SIC3 FE			Yes			Yes			Yes
Estimation	IV	IV	IV	IV	IV	IV	IV	IV	IV
Instrument	Level MPS_t^{orth}	Level 10-yr T-Yield Surp$_t$		Level MPS_t^{orth}	Level 10-yr T-Yield Surp$_t$		Level MPS_t^{orth}	Level 10-yr T-Yield Surp$_t$	
Kleibergen-Paap Wald F stat.	790	40,230	470	790	40,230	431	653	40,402	393
No. of obs.	317,494	175,568	248,480	317,494	175,568	248,480	255,870	138,466	202,730

Notes: This table shows robustness checks for the relationship between interest rates and institutional investors' investment behavior, i.e., equation 3.3.1. In columns (1) to (3), the dependent variable $Log(1+Bonds)_{j,s,t}$ is the natural logarithm of 1 plus the par value held by investor *j* in security *s* at the end of quarter *t*. In columns (4) and (5), the dependent variable $\mathbf{1}(Bonds_{j,s,t})$ is an indicator variable that takes the value of 1 if investor *j* holds any positive amount of bond *s* at the end of quarter *t*, i.e., the extensive margin. In columns (6) and (7), the dependent variable $Log(Bonds)_{j,s,t}$ is the natural logarithm of the par value of bond *s* held by investor *j* at the end of quarter *t*, i.e., the intensive margin. *10-yr T-Yield*$_t$ denotes the 10-year U.S. Treasury yield at the end of quarter *t*. $\mathbf{1}(Mutual\ funds_j)$ is an indicator variable that takes the value of 1 if investor *j* represents the aggregate investments of mutual funds. In columns (1), (4), and (7), we instrument *10-yr T-yield*$_t$ with *Level* MPS_t^{orth}, the cumulative sum of all monetary policy shocks identified by Bauer and Swanson (2023) until quarter *t*. In all other columns, we instrument *10-yr T-yield*$_t$ with *Level 10-yr T-Yield Surp*$_t$, the cumulative sum of all high-frequency changes in the 10-year U.S. Treasury yield around FOMC meetings from Bauer and Swanson (2023) until quarter *t*. We control for bond characteristics and bond supply with security-time fixed effects. Additionally, we control for investors' preferences by including investor-maturity and investor-rating fixed effects. A security's maturity is the remaining maturity of bond *s* at the end of quarter *t* clustered into the following buckets: 0-1 years, 1-3 years, 3-5 years, 5-10 years, 10-15 years, 15-20 years, and greater than 20 years. We control for several lagged macro variables, *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the investor-firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.C.3. Investors' demand for bonds in response to monetary policy across maturities

	Dependent variable				
	$\text{Log}(1+\text{Bonds})_{j,s,t}$			Extensive margin	Intensive margin
Maturity:	<3 y'rs	3-10 y'rs	>10 y'rs	3-10 y'rs	
	(1)	(2)	(3)	(4)	(5)
$\mathbf{1}(\text{Mutual funds}_j) \times$ 10-yr T-Yield_t	-0.526	-0.877**	0.073	-0.018	-0.661***
	[1.21]	[0.41]	[0.96]	[0.03]	[0.11]
Investor × Macro controls	Yes	Yes	Yes	Yes	Yes
Security-Time FE	Yes	Yes	Yes	Yes	Yes
Investor-Security-Year FE	Yes	Yes	Yes	Yes	Yes
Investor-Security-Season FE	Yes	Yes	Yes	Yes	Yes
Investor-Maturity FE	Yes	Yes	Yes	Yes	Yes
Investor-Rating FE	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV
Instrument	Level 10-yr T-Yield Surp_t				
Kleibergen-Paap rk Wald F stat.	37	242	95	242	203
No. of obs.	49,898	155,636	75,030	155,636	127,120

Notes: This table shows estimates for the relationship between interest rates and institutional investors' investment behavior. In columns (1) to (3), the dependent variable $Log(1+Bonds)_{j,s,t}$ is the natural logarithm of 1 plus the par value held by investor j in security s at the end of quarter t. In column (4), the dependent variable $\mathbf{1}(Bonds_{j,s,t})$ is an indicator variable that takes the value of 1 if investor j holds any positive amount of bond s at the end of quarter t, i.e., the extensive margin. In column (5), the dependent variable $Log(Bonds)_{j,s,t}$ is the natural logarithm of the par value of bond s held by investor j at the end of quarter t, i.e., the intensive margin. *10-yr* $T\text{-}Yield_t$ denotes the 10-year U.S. Treasury yield at the end of quarter t. $\mathbf{1}(Mutual\ funds_j)$ is an indicator variable that takes the value of 1 if investor j represents the aggregate investments of mutual funds. We instrument *10-yr* $T\text{-}yield_t$ with *Level 10-yr T-Yield* $Surp_t$, the cumulative sum of all high-frequency changes in the 10-year U.S. Treasury yield around FOMC meetings from Bauer and Swanson (2023) until quarter t. We control for bond characteristics and bond supply with security-time fixed effects. Additionally, we control for investors' preferences by including investor-maturity and investor-rating fixed effects. A security's maturity is the remaining maturity of bond s at the end of quarter t clustered into the following buckets: 0-1 years, 1-3 years, 3-5 years, 5-10 years, 10-15 years, 15-20 years, and greater than 20 years. We control for several lagged macro variables, i.e., ΔGDP, ΔPCE, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the investor-firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.C.4. Investors' demand for bonds in response to monetary policy across credit ratings

	Dependent variable					
	$\text{Log}(1+\text{Bonds})_{j,s,t}$		Extensive margin		Intensive margin	
Credit rating:	IG	HY	IG	HY	IG	HY
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}(\text{Mutual funds}_j) \times$ 10-yr T-Yield$_t$	-0.120	-1.352***	0.013	-0.034	-0.378***	-1.090***
	[0.52]	[0.52]	[0.03]	[0.03]	[0.12]	[0.20]
Investor × Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Security-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Security-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Security-Season FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Investor-Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV	IV
Instrument	Level 10-yr T-Yield Surp$_t$					
Kleibergen-Paap rk Wald F stat.	280	112	280	112	168	65
No. of obs.	141,394	147,696	141,394	147,696	113,112	117,184

Notes: This table shows estimates for the relationship between interest rates and institutional investors' investment behavior. In columns (1) and (2), the dependent variable $Log(1+Bonds)_{j,s,t}$ is the natural logarithm of 1 plus the par value held by investor j in security s at the end of quarter t. In columns (3) and (4), the dependent variable $\mathbf{1}(Bonds_{j,s,t})$ is an indicator variable that takes the value of 1 if investor j holds any positive amount of bond s at the end of quarter t, i.e., the extensive margin. In columns (5) and (6), the dependent variable $Log(Bonds)_{j,s,t}$ is the natural logarithm of the par value of bond s held by investor j at the end of quarter t, i.e., the intensive margin. *10-yr T-Yield*$_t$ denotes the 10-year U.S. Treasury yield at the end of quarter t. $\mathbf{1}(\textit{Mutual funds}_j)$ is an indicator variable that takes the value of 1 if investor j represents the aggregate investments of mutual funds. We instrument *10-yr T-yield*$_t$ with *Level 10-yr T-Yield Surp*$_t$, the cumulative sum of all high-frequency changes in the 10-year U.S. Treasury yield around FOMC meetings from Bauer and Swanson (2023) until quarter t. We control for bond characteristics and bond supply with security-time fixed effects. Additionally, we control for investors' preferences by including investor-maturity and investor-rating fixed effects. A security's maturity is the remaining maturity of bond s at the end of quarter t clustered into the following buckets: 0-1 years, 1-3 years, 3-5 years, 5-10 years, 10-15 years, 15-20 years, and greater than 20 years. We control for several lagged macro variables, i.e., *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the investor-firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.C.5. Drivers of difference in growth rates

Dep. variable:	$(g_{I,t} - g_{MF,t})$	
	(1)	(2)
$g_{I,t}$	0.797*	
	[0.47]	
$g_{MF,t}$		-0.973***
		[0.06]
Constant	-0.026**	0.011**
	[0.01]	[0.00]
R^2	0.078	0.878
Adj. R^2	0.051	0.875
No. of obs.	36	36

Notes: This table shows the relationship between the investors' growth rates and the main explanatory variable in the spillover analysis. The dependent variable, $(g_{I,t} - g_{MF,t})$, is the difference in the growth rates of insurers' and mutual funds' corporate bond holdings of nonfinancial institutions in quarter t. $g_{I,t}$ ($g_{MF,t}$) is the growth rate of insurers' (mutual funds') aggregate corporate bond holdings of nonfinancial institutions from quarter $t-1$ to t. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3.C.6. Robustness: Relationship as a driver of the spillovers

	Dependent variable			
	1(New $loan_{b,l,t+1}$)	Log(1+ $Loan)_{b,l,t+1}$	**1**(New $loan_{b,l,t+1}$)	Log(1+ $Loan)_{b,l,t+1}$
Subsample:	No previous relationship		Existing relationship	
	(1)	(2)	(3)	(4)
Insurer $share_{b,t-1} \times (g_{I,t} - g_{MF,t})$	-0.895*	-17.095*	-1.509*	-29.642*
	[0.49]	[9.36]	[0.84]	[15.90]
Insurer $share_{b,t-1}$	-0.165***	-3.104***	-0.023	-0.443
	[0.05]	[1.02]	[0.04]	[0.77]
Lender-Time FE	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes
Borrower-Year FE	Yes	Yes	Yes	Yes
Borrower-Season FE	Yes	Yes	Yes	Yes
Macro controls × Insurer share	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes
Borrower rating	Yes	Yes	Yes	Yes
Borrower controls × QE	Yes	Yes	Yes	Yes
Borrower rating × QE	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV
Instrument	10-yr T-Yield $Surp_t$			
Kleibergen-Paap rk Wald F stat.	471	471	54	54
No. of obs.	105,489	105,489	108,381	108,381

Notes: This table analyzes the drivers of the relationship between changes in investors' corporate bond demand and firms' loan demand. In columns (1) and (3), the dependent variable, **1**(*New* $loan_{b,l,t+1}$), is an indicator variable that is equal to 1 if at least one syndicated loan is granted by lender l to borrower b within quarter $t + 1$. In columns (2) and (4), the dependent variable, *Log(1+Loan)*$_{b,l,t+1}$, is the natural logarithm of 1 plus the loan amount granted by lender l to borrower b in quarter $t + 1$. *Insurer share*$_{b,t-1}$ is the share of firm b's bonds held by insurers out of the total amount of bonds held by insurers and mutual funds at the end of quarter $t - 1$. The independent variable $(g_{I,t} - g_{MF,t})$ is the difference in the growth rates of insurers' and mutual funds' corporate bond holdings in nonfinancial institutions in quarter t. We instrument $(g_{I,t} - g_{MF,t})$ with *10-yr T-Yield Surp*$_t$, the sum of all high-frequency changes in the 10-year U.S. Treasury market yield over quarter t. We control for several lagged borrower characteristics, i.e., *Log(Assets)*, *Log(Sales)*, *Log(Cash)*, *Leverage* and *Long-term debt*, the lagged median borrower *Rating*, and macroeconomic conditions, i.e., *ΔGDP*, *ΔPCE*, and the *EBP* by Favara, Gilchrist, Lewis, and Zakrajsek (2016). We cluster standard errors at the borrower level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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