Insurers Use Banks for Portfolio Diversification

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Abstract

Insurance companies hold a significant share of the financial sector's long-term bond debt ("finance bonds"). Yet, little is known about the determinants of insurers' investment in finance bonds. Using detailed regulatory data on US insurers, I document that small insurers invest disproportionately in finance bonds. As insurers grow, they extend their portfolios to other industries and eventually underweight finance bonds relative to the market. Exploiting a regulatory reform in 2017 that extended insurers' access to bond exchange-traded funds, I show that finance bonds became less attractive to small insurers. This suggests that finance bonds are an implicit means of diversification, especially for small insurers. I develop a model that rationalizes these observations as the outcome of insurers' portfolio diversification subject to transaction-cost minimization. The model predictions are borne out in the data, supporting the hypothesis that insurers view finance bonds as a diversification tool.

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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). 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.

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 very 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,

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

I follow the approach from Becker and Ivashina (2015) and Becker et al. (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 et al. (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

2 Warren Buffett, in his 2002 letter to the shareholders of Berkshire Hathaway, made the importance of the underwriting business very 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

as Che and Liebenberg (2017), Elango et al. (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 et al. (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 very 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 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 et al. (2018), Fuster et al.

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)

(2019)), regulation (Ordoñez (2018), Irani et al. (2021), de Roure et al. (2022), Chen et al. (2023)), heterogeneous exposure to monetary policy (Chen et al. (2018), Nelson et al. (2018), Elliott et al. (2022), Elliott et al. (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 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 et al. (2011), Fache Rousová and Giuzio (2019), Chodorow-Reich et al. (2021)) and the associated real effects (Kubitza (2023), Massa and Zhang (2021), Manconi et al. (2016), Liu et al. (2021)). Moreover, Ellul et al. (2022) and Kubitza et al. (2023) show that certain contractual features of life insurance products increase systemic risk and the probability of fire sales. Girardi et al. (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 et al. (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 et al. (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 (see Sen (2022), Becker et al. (2022), Knox and Sørensen (2024), Ellul et al. (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

3 Related strands in this literature have studied drivers of insurers' price setting (e.g., Froot and O'Connell (1999), Froot (2001), Oh et al. (2023), Knox and Sørensen (2024), Ge (2022), Giambona et al. (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 et al. (2020)), and insurance regulation (e.g., Tenekedjieva (2021), Leverty and Grace (2018)).

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.

The remainder of this paper is organized as follows. In Section 2, I describe the main data and provide four novel stylized facts. In Section 3, I exploit a regulatory reform to provide the first causal evidence. Motivated by the empirical facts, Section 4 presents a model that explains the observed patterns and derives further predictions. In Sections 5 and 6, I take the model's predictions to the data and conduct several empirical tests that back up the model's mechanism. Section 7 rules out alternative explanations. Section 8 concludes the paper.

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.

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 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.

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 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 C.1). There are substantially more property & 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.

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 2 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.

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 3). However, panel (b) of Figure 3 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

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.

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 4 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 4 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 B.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 4, I regress insurers' portfolio shares, Share_{ist}, on a set of interactions of industry dummies with insurers' size $\mathit{Log(Assets)}_{it}$,

$$\text{Share}_{ist} = \sum_{s} \beta_s \cdot \mathbb{1}\{\text{Industry} = s\} \cdot \text{Log(Assets)}_{it} + \beta_{Missing} \cdot \text{Log(Assets)}_{it} + \gamma \boldsymbol{X}_{it} + u_{is} + v_t + \epsilon_{it}. \quad (1)$$

$\mathbb{1}\{\text{Industry} = s\}$ 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 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.

Essentially, the coefficients of equation 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

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).

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 5 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 5, the smaller insurer invests on average 3 percentage points less of her corporate bond portfolio in finance bonds and more in other industries. In Table 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 C.2, I measure the dependent variable $Share_{ist}$ in regression 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 B.3). From these observations, I derive the second fact.

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

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 6 plots the average portfolio yield of 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.

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

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 et al. (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,

$$\text{Share issue}_{b;k} = \beta \cdot \text{Finance}_b + \gamma \cdot \text{Yield spread}_b + \delta \cdot \boldsymbol{X} + u_t + v_{mr} + \epsilon_b, \tag{2}$$

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] $\boldsymbol{X}$ 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 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 C.4, C.5, and C.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 B.4 plots the estimates for the βs of equation 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.*

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7 Panel 1 of Table C.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 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.

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.

$$R_{bt} - R_{ft} = \beta_{b0} + \beta_{Market} \cdot \text{Market spread}_t + \beta_{Default} \cdot \text{Default spread}_t + \beta_{Term} \cdot \text{Term spread}_t + \epsilon_{bt}. \quad (3)$$

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,

$$R_{bt} = \frac{(P_{bt} + AI_{bt}) + C_{bt} - (P_{bt} + AI_{bt-1})}{(P_{bt-1} + AI_{bt-1})}, \quad (4)$$

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 3, I estimate the error terms ϵ_{bt} and use the time series variance, $\sigma(\hat{\epsilon})_b$, as the proxy for idiosyncratic risk.[10]

Panel (a) of Figure 7 shows that finance bonds have one of the lowest median $\sigma(\hat{\epsilon})_b$ among industries. Finance bonds have the second-lowest median $\sigma(\hat{\epsilon})_b$ 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 7).

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

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 C.3 provides the summary statistics of idiosyncratic risk variables.

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,

$$\sigma(\hat{\epsilon})_b = \beta \cdot \text{Finance}_b + \gamma \cdot \boldsymbol{X}_b + u_{ymr} + v_{gy} + \epsilon_b. \tag{5}$$

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 $\sigma(\hat{\epsilon})_b$ is the estimated variance of the idiosyncratic error term in the returns multiplied by 100.

One potential concern regarding equation 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 3 shows the results of regression equation 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 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 C.7 and C.8 show the results of two robustness checks. In Table C.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 et al. (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

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 et al. (2022) show that SIFIs' funding costs and credit spreads still reflect investors' expectations of an implicit government guarantee. However, Berndt et al. (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.

C.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 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.

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 invest in bond ETFs. Earley et al. (2017) report that some insurers even replaced their entire bond portfolio with bond ETFs. Figure 8 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 very 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)).

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

$$\text{Share issue}_{b;k} = \beta_{Post} \cdot \text{Post}_t \cdot \text{Finance}_b + \beta_{Pre} \cdot \text{Finance}_b + \gamma \cdot \text{Treasury spread}_b + \delta \cdot \boldsymbol{X} + u_t + v_{mr} + \epsilon_b. \quad (6)$$

13 Figure B.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.

15 My data on insurers’ bond ETF investments does not contain any ETF investments prior to 2011.

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 8 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 9 visualizes the results of equation 6. 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 B.5 in the Online Appendix repeats equation 6 but includes all sample years. The results are qualitatively similar. The reform has made finance bonds less attractive for small insurers.

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.

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.

$$R_i = \beta_{i0} + \sum_{k=1}^{K} \beta_{ik} f_k + \epsilon_i. \tag{7}$$

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 et al. (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

$$\sum_i w_{Bi}\tilde{R}_i < \frac{D}{D+B} \cdot r + \frac{B}{D+B} \cdot R_B. \tag{8}$$

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

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 et al. (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.

with loadings $(\beta_{L0}, \beta_{L1}, \ldots, \beta_{LK})$, and an idiosyncratic error term ϵ_L, i.e.

$$\mu_L = \beta_{L0} + \sum_{k=1}^{K} \beta_{Lk} f_k + \epsilon_L. \tag{9}$$

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,

$$\max_{\boldsymbol{w_I}} \quad E\Big[A_0\Big(\underbrace{\sum_{i=1}^{N} w_{Ii}\tilde{R}_i - \mathbb{1}\{w_{Ii} > 0\}\frac{c}{A_0}}_{\text{=net return risky assets}} + \underbrace{w_{IB}\tilde{R}_B - \mathbb{1}\{w_{IB} > 0\}\frac{c}{A_0}}_{\text{=net return bank bonds}}\Big) - \tilde{L}_1 - \underbrace{K\Big(\frac{\tilde{A}_1}{\tilde{L}_1}\Big)}_{\text{=reg. cost}}\Big]. \tag{10}$$

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 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

19 Figure B.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.

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.

4.2 Computational solution

Parameter choices. Because there is no analytical solution for the maximization problem 10, 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. 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

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

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 10 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. $c = 0$.

Panel (b) of Figure 10 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 10 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 10 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.*

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.

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 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

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

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.

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 4 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,

$$\begin{aligned}\text{Share}_{ist} = &\sum_s \beta_s \cdot \mathbb{1}\{\text{Industry} = s\} \cdot \text{Liability risk}_{it} + \beta_{Missing} \cdot \text{Liability risk}_{it} \\ &+ \sum_s \gamma_s \cdot \mathbb{1}\{\text{Industry} = s\} \cdot \text{Log(Assets)}_{it} + \gamma_{Missing} \cdot \text{Log(Assets)}_{it} + \gamma \boldsymbol{X}_{it} + u_i + v_{st} + w_{ht} + \epsilon_{ist}.\end{aligned} \tag{11}$$

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 11 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,

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".

the number of states (products) where an insurer writes premiums must be negatively related to the investments in finance bonds.

Panel 1 of Table 5 shows the estimates of equation 11 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 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 11 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.

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 et al. (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 B.7).

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 B.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 11 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 C.9, I formally test the importance of access to external capital for insurers and estimate regression 11 but replace *Liability risk*$_{it}$ with dummy variables *Group member*$_{it}$ or *Stock*$_{it}$. *Group member*$_{it}$ (*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 11. 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 *Stock*$_{it}$ and *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 might exploit this discretion and not diversify enough. Hence, mutual insurers would tilt away from finance bonds.

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

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.

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 et al. (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 et al. (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

$$\text{Friction}_f = 1 - \frac{\text{Rate}\Delta\text{Received}_f}{\text{Rate}\Delta\text{Target}_f}, \tag{12}$$

where $\textit{Rate}\Delta\textit{Target}_f$ is the target rate calculated by the insurer in filing f and $\textit{Rate}\Delta\textit{Received}_f$ is the rate accepted by the regulator in filing f. I winsorize the $\textit{Friction}_f$ variable on the 1% and 99% levels. Then, I take for each state the average of $\textit{Friction}_f$ over all filings that were issued in state s between 2010 and 2019. $\textit{Friction}_s$ denotes this average for state s. To compute the average, I only consider filings where $\textit{Rate}\Delta\textit{Received}_f$ and $\textit{Rate}\Delta\textit{Target}_f$ have both been positive and $\textit{Rate}\Delta\textit{Received}_f$ has been lower or equal than $\textit{Rate}\Delta\textit{Target}_f$. First, this accounts for rate filings with a negative $\textit{Rate}\Delta\textit{Target}_f$ which should not be motivated by insurers' increased business risk. Second, a situation where $\textit{Rate}\Delta\textit{Received}_f$ is larger than $\textit{Rate}\Delta\textit{Target}_f$ 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 $\textit{Friction}_s$.

The main changes compared to Oh et al. (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 $\textit{Friction}_s$. 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. $\textit{High (Low) friction}_{it}$ 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.

$$\begin{aligned}\text{Finance share}_{it} = {} & \beta_C \cdot \text{Pricing constraint}_{it-1} + \beta_A \cdot \text{Log(Assets)}_{it} \\ & + \beta_{C\times A} \cdot \text{Pricing constraint}_{it-1} \times \text{Log(Assets)}_{it} + \gamma \cdot \boldsymbol{X}_{it} + u_i + v_t + \epsilon_{it}.\end{aligned} \tag{13}$$

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

I expect β_C to be positive (negative) for $\textit{High friction}_{it-1}$ ($\textit{Low friction}_{it-1}$), 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

25 Oh et al. (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.

as much. Table 6 shows the estimates for regression equation 13. 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 et al. (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 13 for the subsamples of independent insurers and insurance group members. The results are printed in Table C.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 et al. (2023) or the shadow insurance idea brought forward by Koijen and Yogo (2016).

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 very 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 portfolios towards the loan portfolio of their parent company. Then, I define

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.

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 E in the Online Appendix.

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 12 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,

$$\text{Share diversified lenders}_{it} = \beta \cdot \text{Log(Assets)}_{it} + \gamma \cdot \boldsymbol{X}_{it} + u_i + v_t + \epsilon_{it}. \tag{14}$$

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 7 provides the estimates for regression equation 14. 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.

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.

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 very 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 et al. (2007), Harris (2015), Hendershott et al. (2020), Pintér et al. (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 13 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 14 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 14 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 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.

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

28 Schestag et al. (2016) extensively discuss the issue of measuring liquidity of corporate bonds from trading data.

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 15 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.

In Table 8, 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.

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.

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

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 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.

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

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FIGURES

Figure 1
Reciprocal importance of insurers' finance bond investments

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.

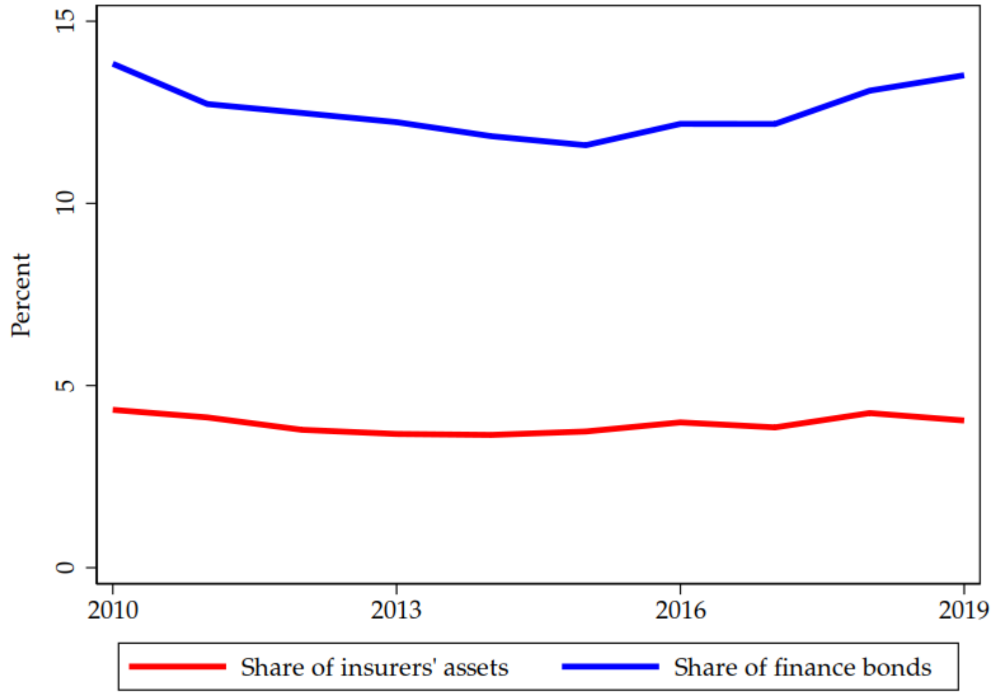


Figure 2
Insurers' portfolio width across size

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

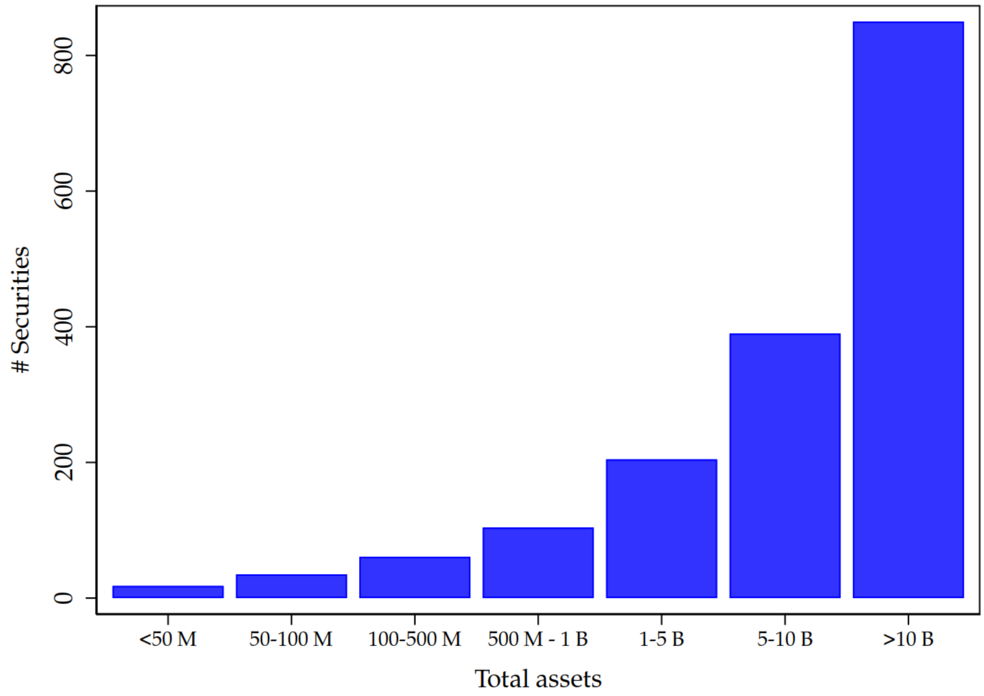
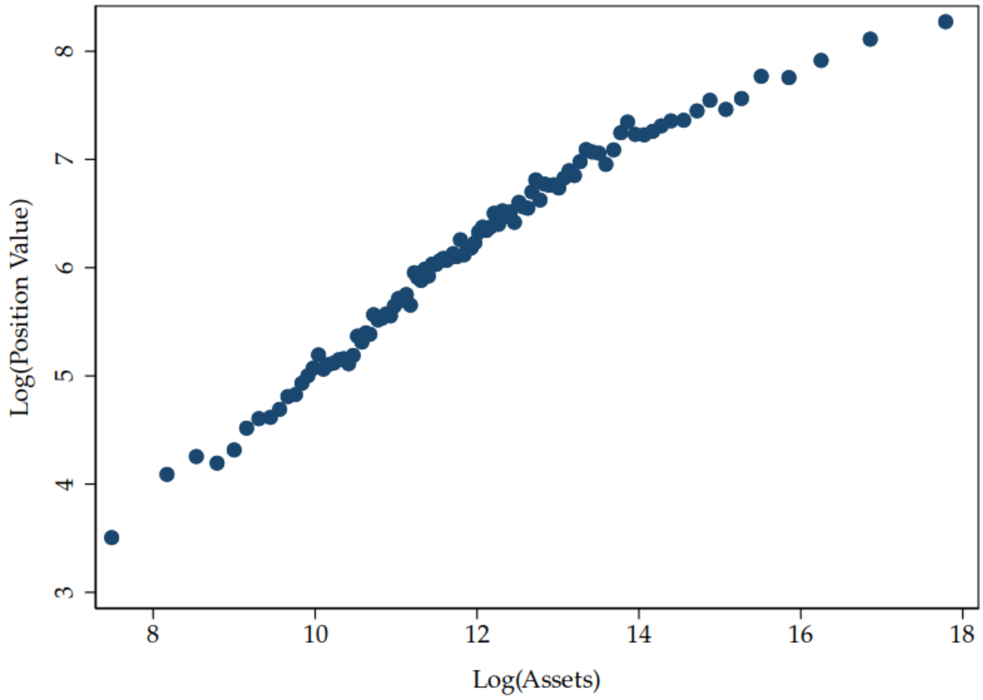
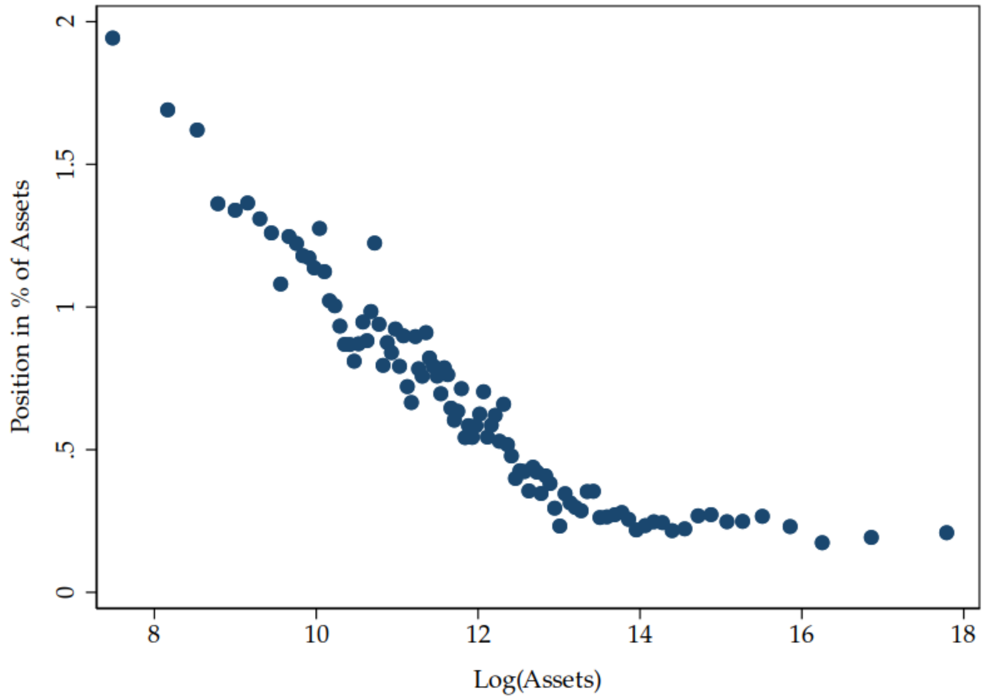


Figure 3
Portfolio position sizes and across insurers' size

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*.



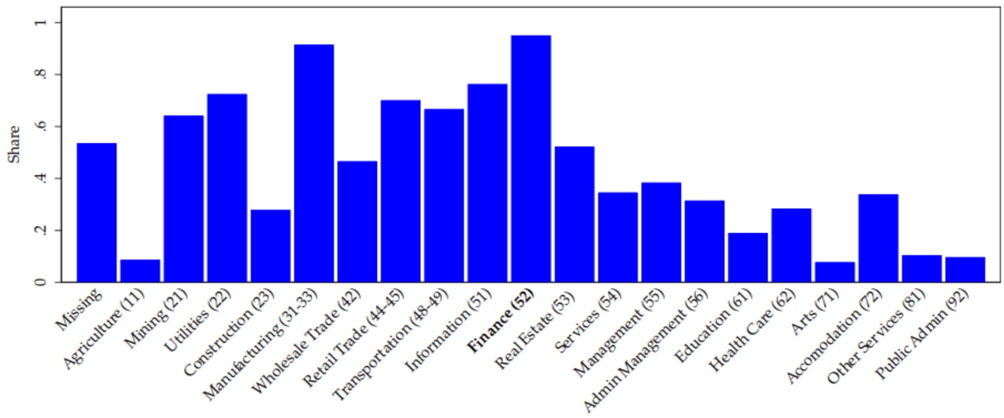
(a) Absolute position size



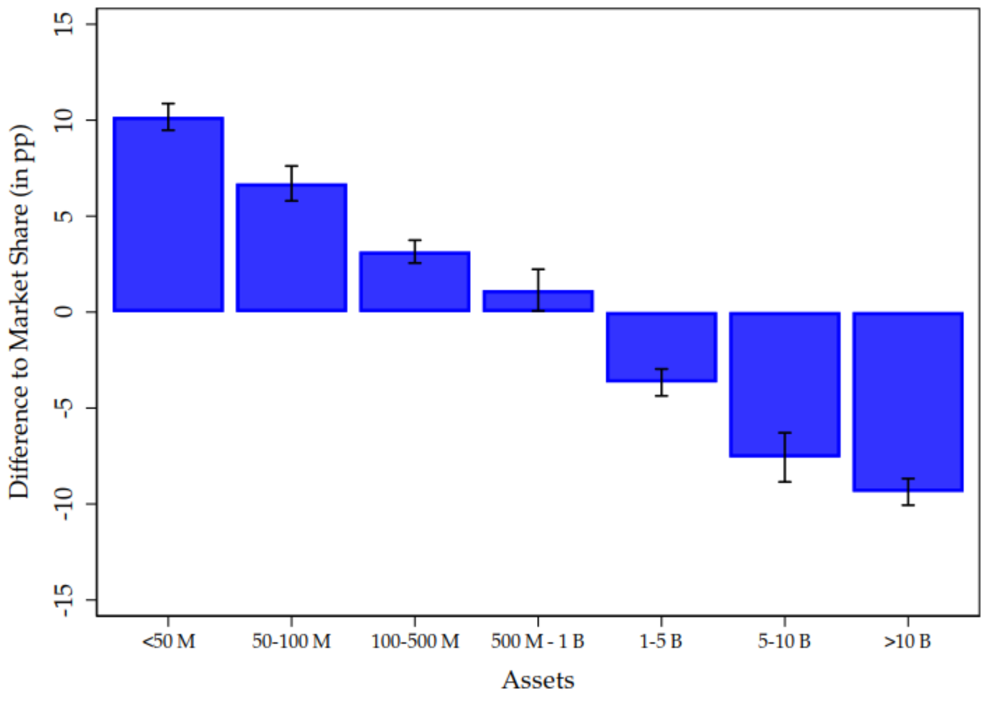
(b) Relative position size

Figure 4
Prevalence of industry sectors and finance bond investments across size

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.



(a) Share of insurers investing in each industry sector



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

Figure 5
Size of insurers and industry portfolio shares

This figure shows the coefficients on the industry interactions and the main term of equation 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.

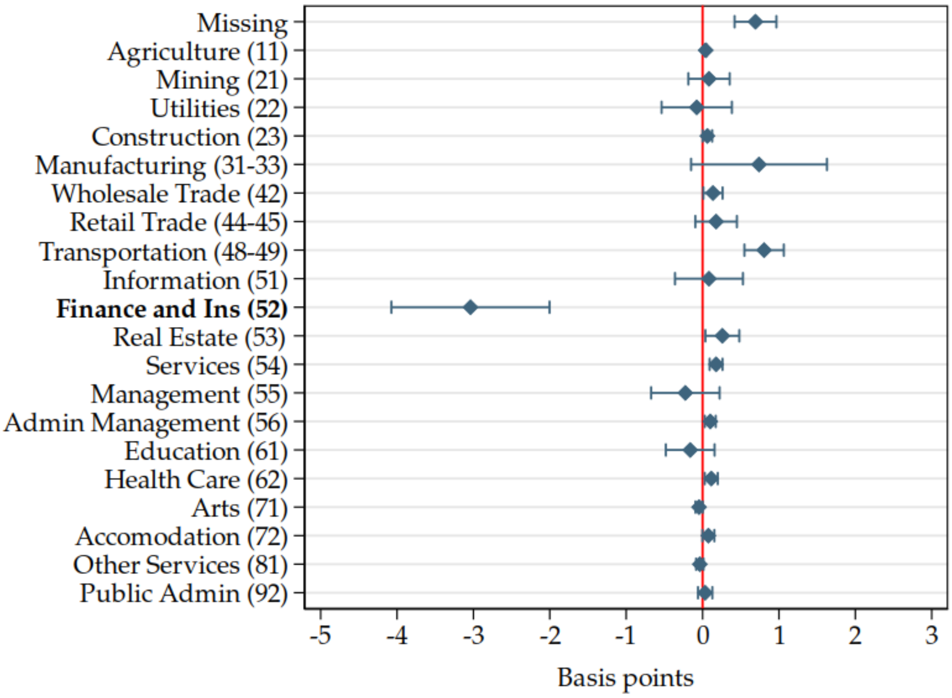
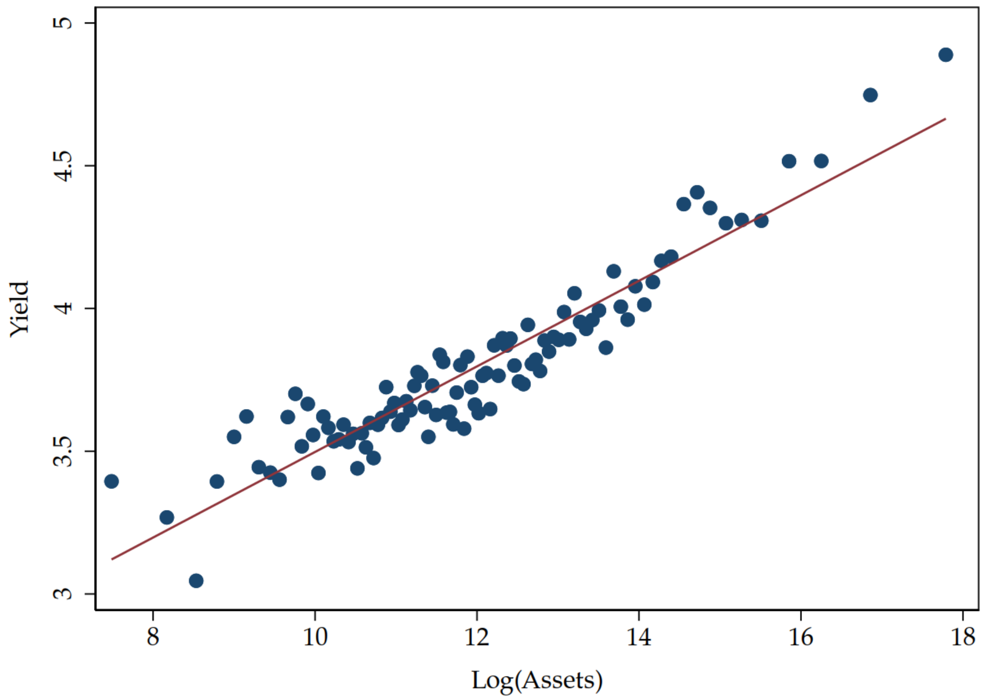
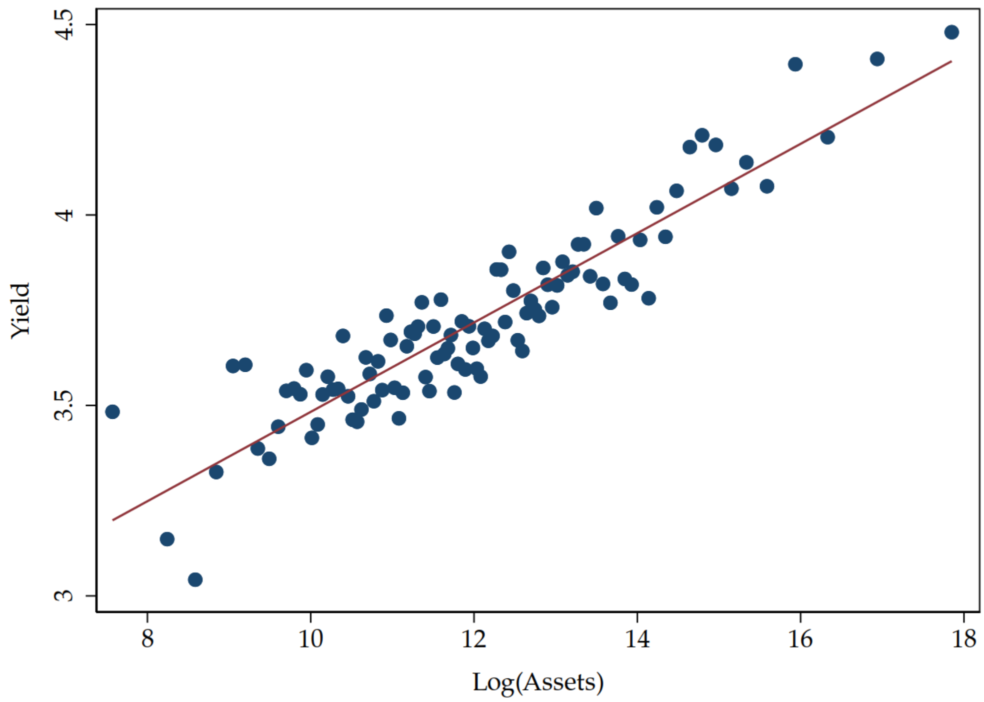


Figure 6
Portfolio yield across size

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.



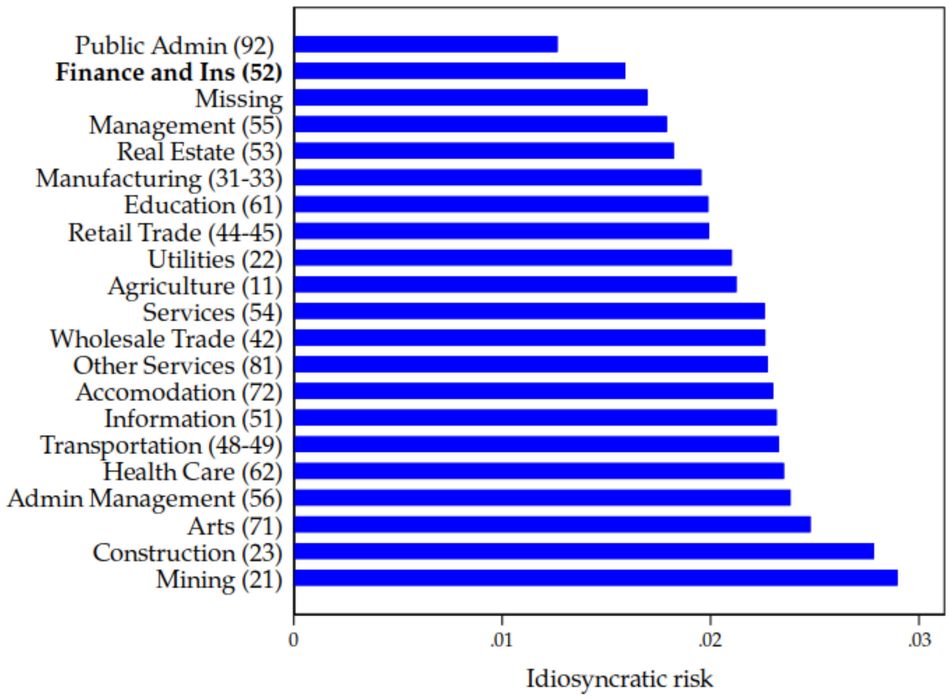
(a) All bonds



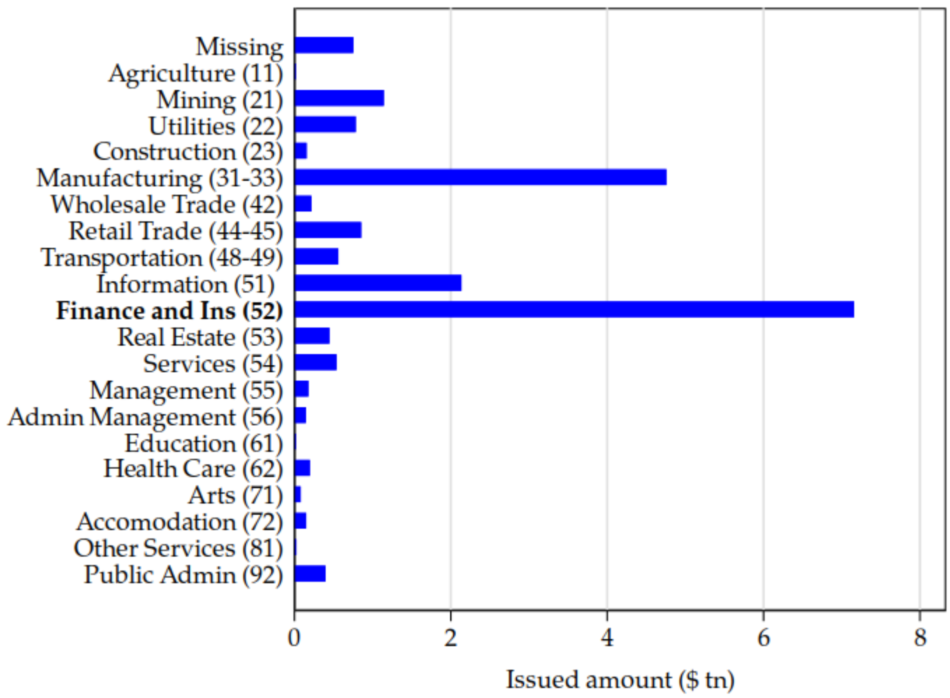
(b) Only finance bonds

Figure 7
Idiosyncratic volatility and bond issuance

This figure plots in panel (a) the median idiosyncratic volatility of large bond issues - 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.



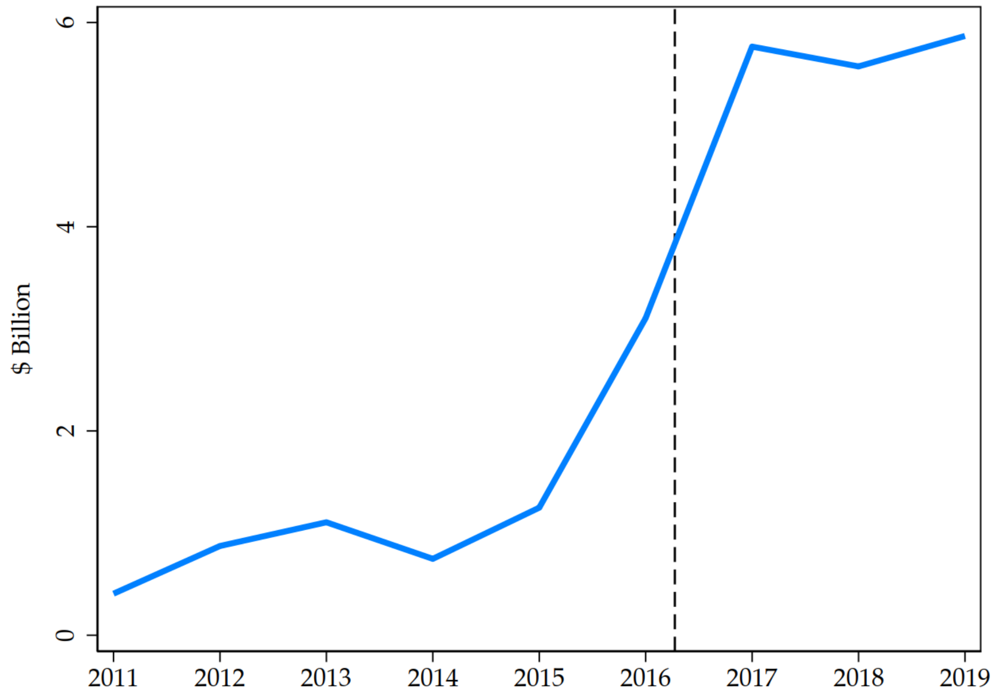
(a) Idiosyncratic volatility by industry



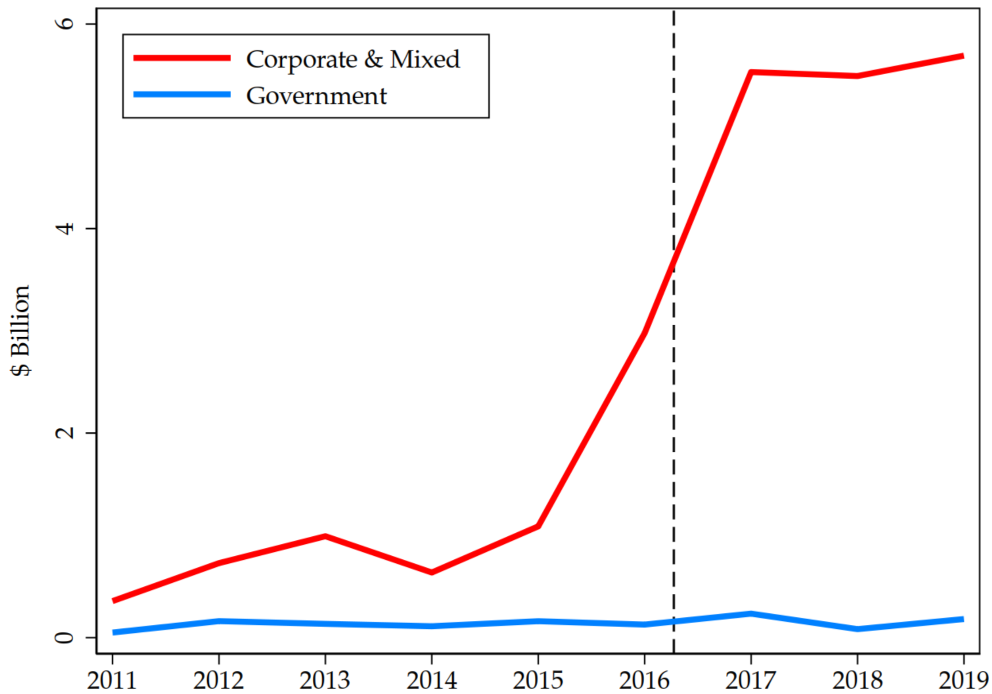
(b) Bond issuance by industry

Figure 8
Total bond ETF investments by insurers

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.



(a) All



(b) By ETF type

Figure 9
Impact of the 2017 NAIC bond ETF reform on the use of finance bonds

This figure plots the β coefficients of regression 6 for the seven different size buckets scaled by the mean of the dependent variable. It replicates the approach from Becker et al. (2022) and considers only new issues proxied for by insurers' year-end holdings in the year of issuance.

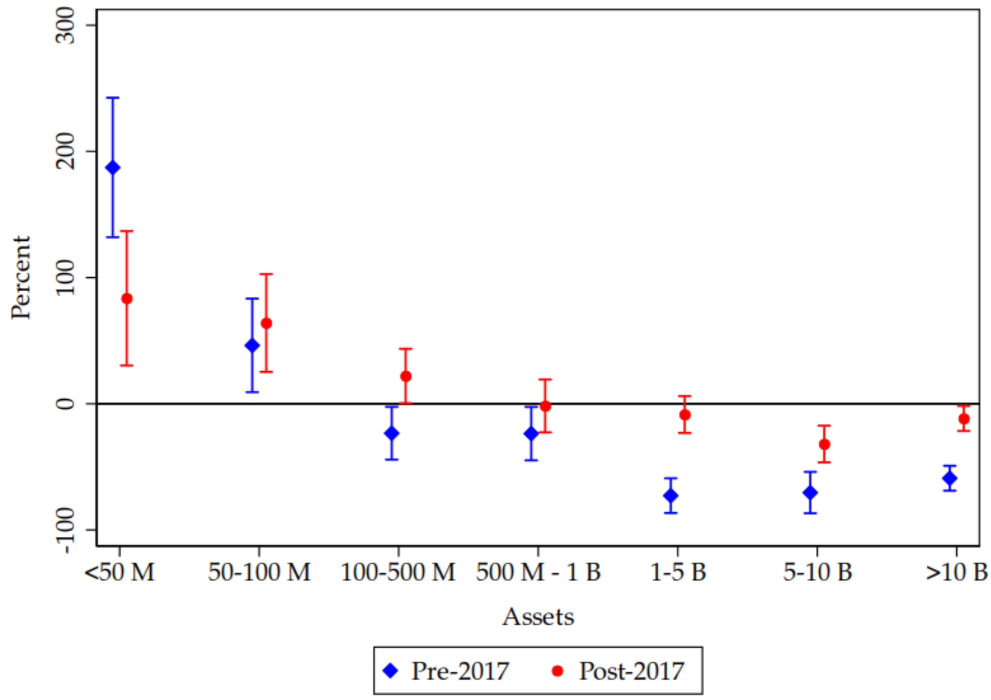
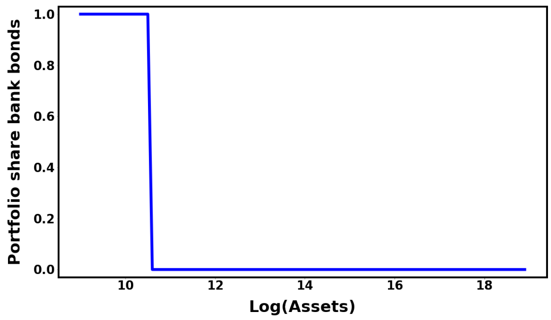
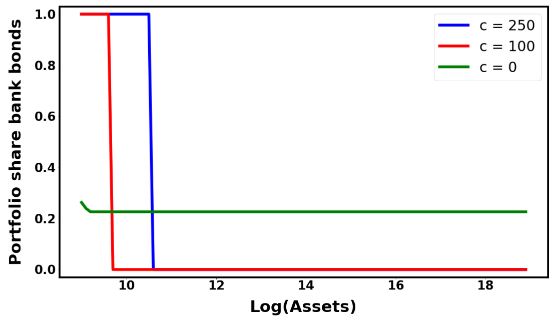


Figure 10
Model simulation

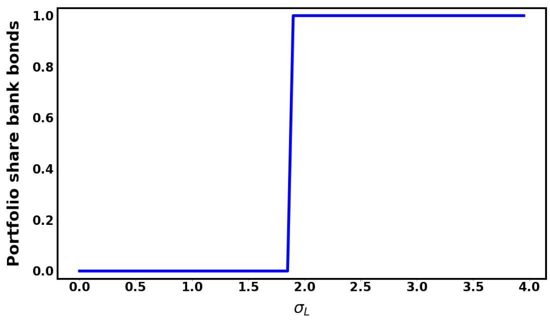
This figure plots the results of the model simulation. Panel (a) shows the results of the baseline scenario, panel (b) of the baseline scenario and two alternative scenarios with lower fixed cost c, panel (c) of a scenario with fixed insurer size A_0 across a grid of values of the idiosyncratic liability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



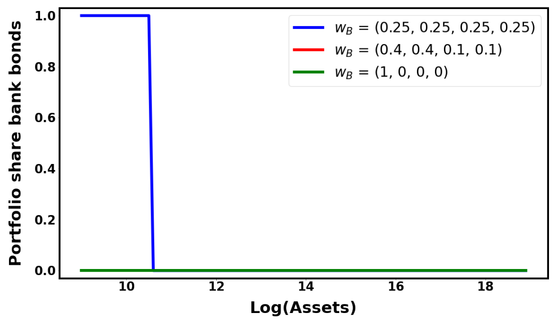
(a) Baseline result



(b) Fixed cost



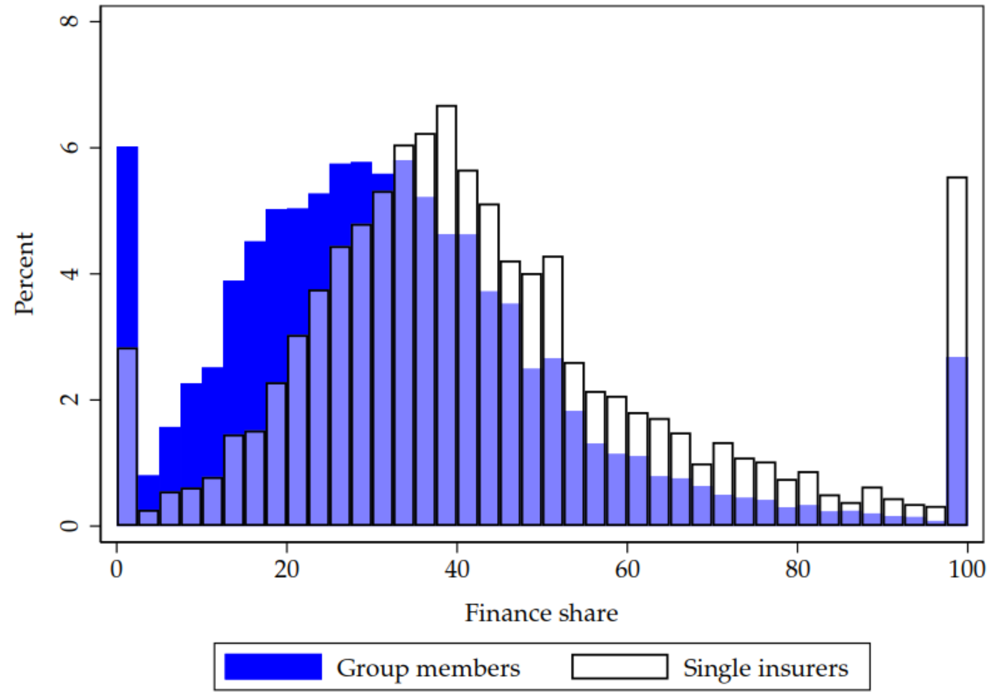
(c) Liability risk



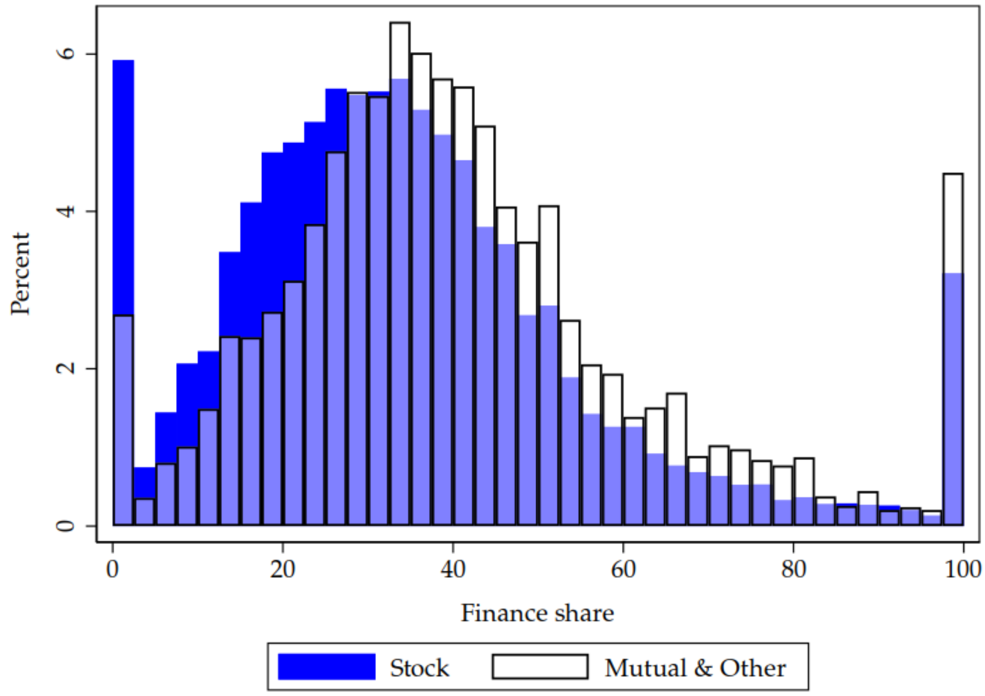
(d) Bank diversification

Figure 11
Insurance groups, stock companies, and Finance investments

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.



(a) Group membership



(b) Organizational structure

Figure 12
Diversification in the finance bond portfolio across size

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.

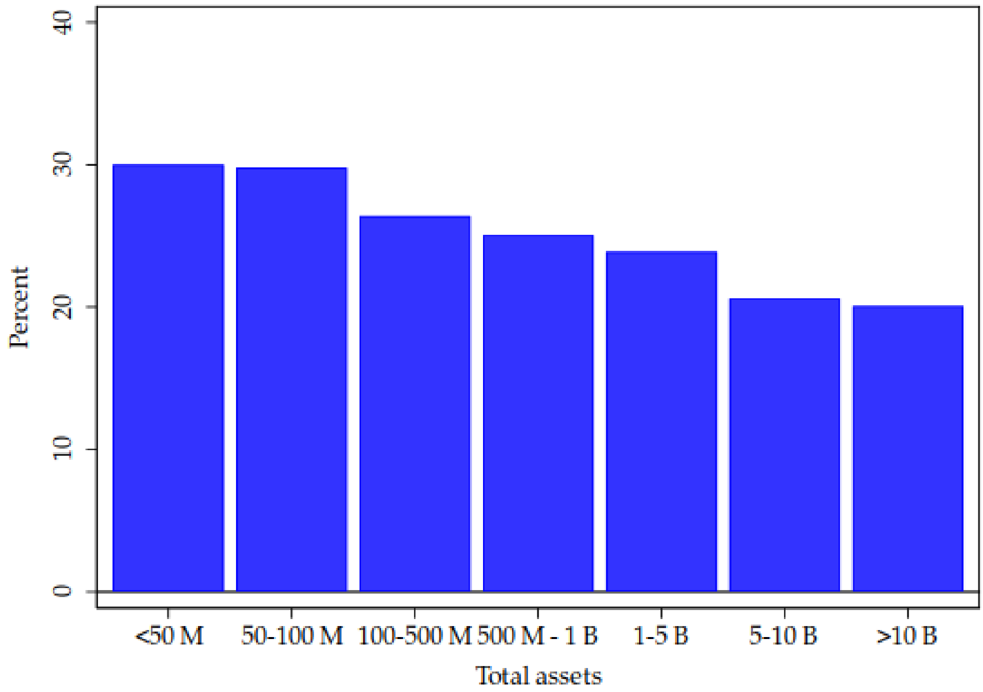


Figure 13
Trading costs of finance bonds versus other industries

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.

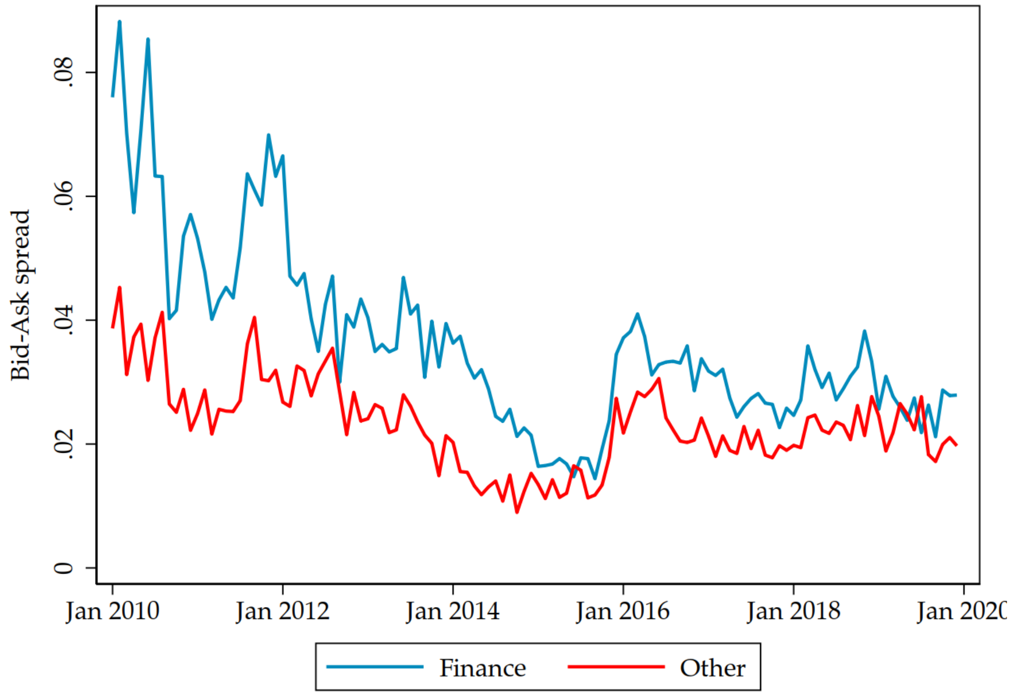


Figure 14
Liquidity of finance bonds versus other industry sectors for small trade sizes

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.

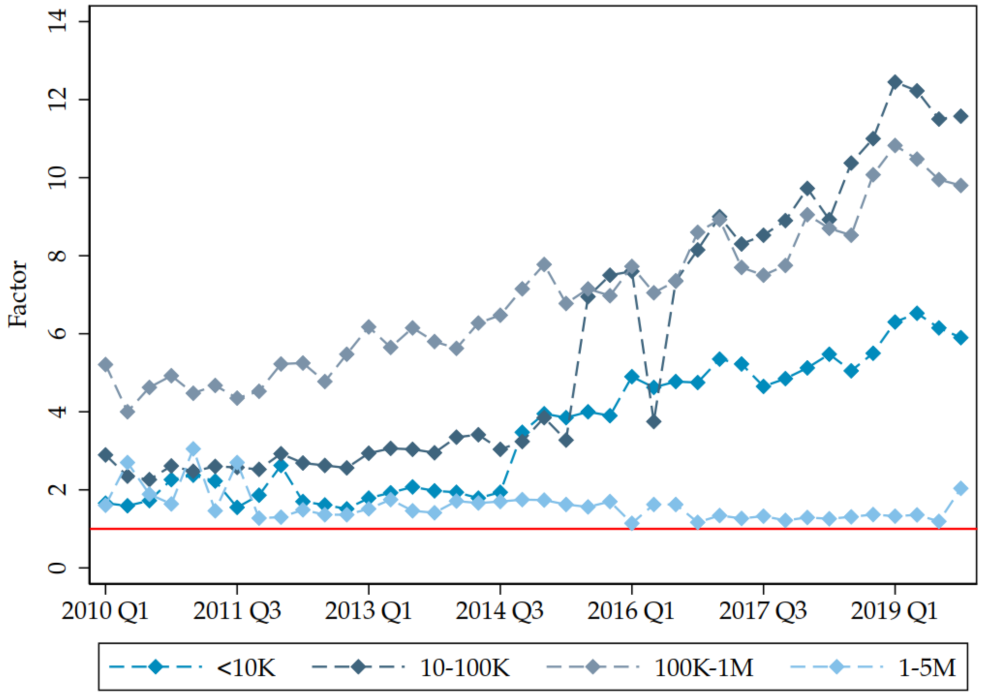
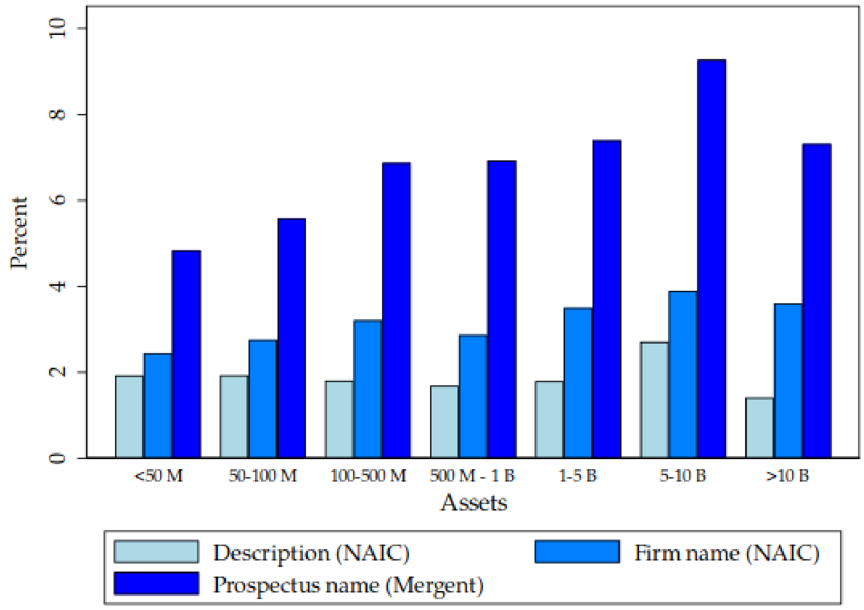
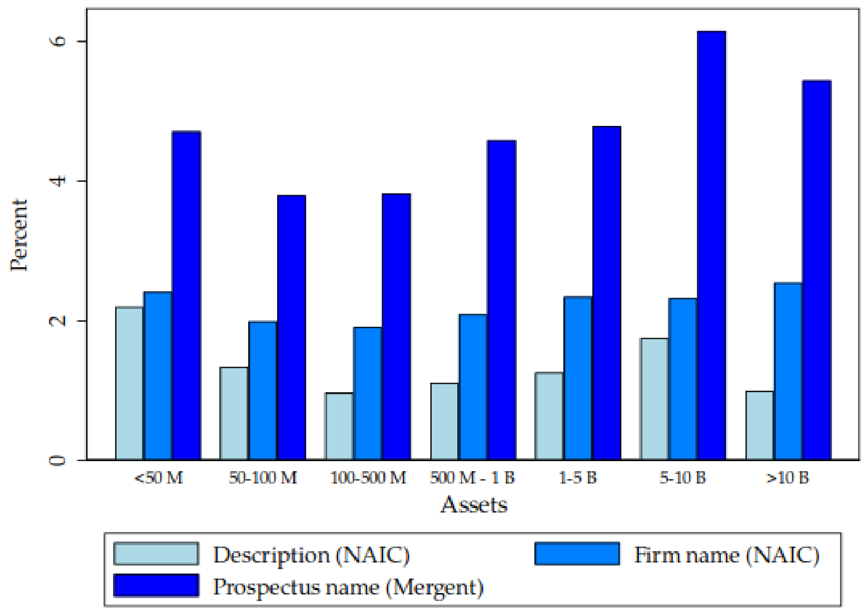


Figure 15
Finance bonds as access to corporate bond markets

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).



(a) Acquisitions



(b) Disposals

TABLES

Table 1
Summary statistics for the insurer-year-level sample

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.

	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								
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								
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

Table 2
Insurers' size and corporate bond portfolio allocation

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*. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	Dependent variable: *Share*$_{ist}$				
	(1)	(2)	(3)	(4)	(5)
Finance$_s$ × 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

Table 3
Idiosyncratic risk of Finance versus other bonds

This table shows estimates for regression equation 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 $\sigma(\hat{\epsilon})_b$ 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. t-statistics are shown in parantheses. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	Dependent variable: $\sigma(\hat{\epsilon})_b$						
			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

Table 4
Summary statistics for risk constraints

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.

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

Table 5
Underwriting risk and finance bond investments

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*. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

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)
$\text{Finance}_s \times \text{Log(Assets)}_{it}$	-2.495***	-2.502***	-2.943***	-2.932***	-2.380***	-2.376***
	[-11.84]	[-11.77]	[-10.23]	[-9.86]	[-9.65]	[-9.53]
$\text{Finance}_s \times \text{Liability risk}_{it}$	0.114**	0.113**	-0.104**	-0.100**	0.129**	0.130**
	[2.31]	[2.20]	[-2.13]	[-1.99]	[2.41]	[2.35]
$\text{Finance}_s \times \text{Liability risk}_{it} \times \text{Log(Assets)}_{it}$	-0.007*	-0.007*	0.006	0.005	-0.008*	-0.008*
	[-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 5 continued.

Panel 2: Business diversification

Risk variable:	Dependent variable: $Share_{ist}$					
	Business HHI$_{it}$		*Active lines*$_{it}$		*Business conc. ratio*$_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Finance$_s$ $\times$ 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]
Finance$_s$ $\times$ 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]
Finance$_s$ $\times$ Liability risk$_{it}$ $\times$ Log(Assets)$_{it}$	-0.011	-0.016**	0.019**	0.022***	-0.009	-0.013**
	[-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

Table 6
Regulatory pricing constraints and Finance share

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*. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	Dependent variable: *Finance share*$_{it}$					
Pricing constraint$_{it-1}$ defined as:	*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$_{it-1}$ × Log(Assets)$_{it}$	-1.944**	-1.731*	-1.812*	1.834	1.936	2.116*
	[-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

Table 7
Intermediated diversification and insurers' size

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*. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	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

Table 8
Liability risk and insurers' choice of finance bonds

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 $t(a)-1$. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	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

A Data and variable definitions

Table A.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 A.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.*

B Additional figures

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

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.

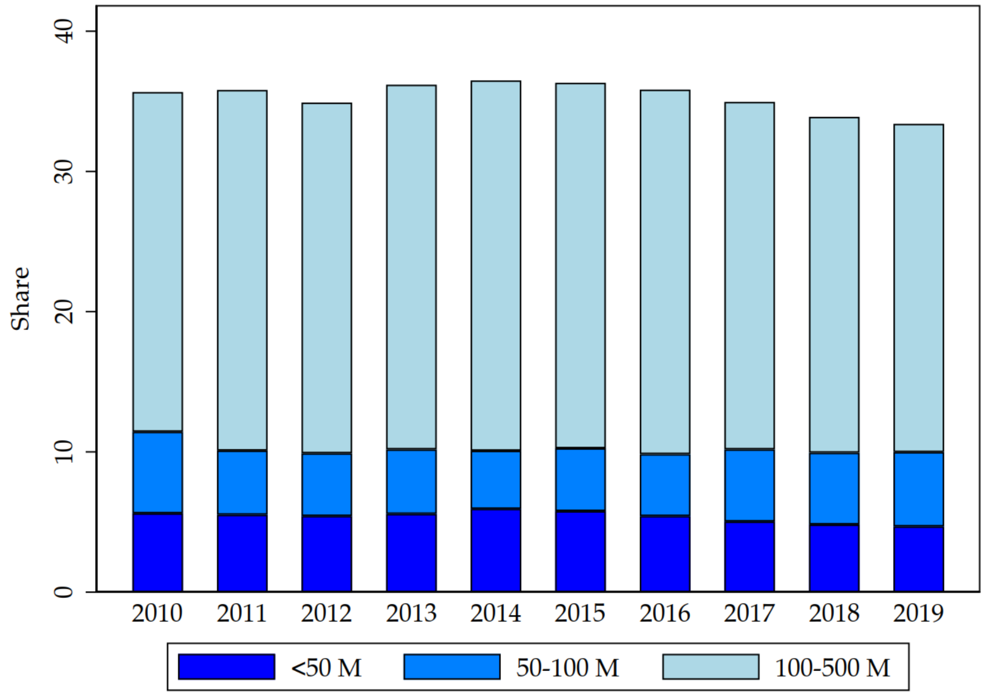


Figure B.2
Finance bonds in the market portfolio

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.

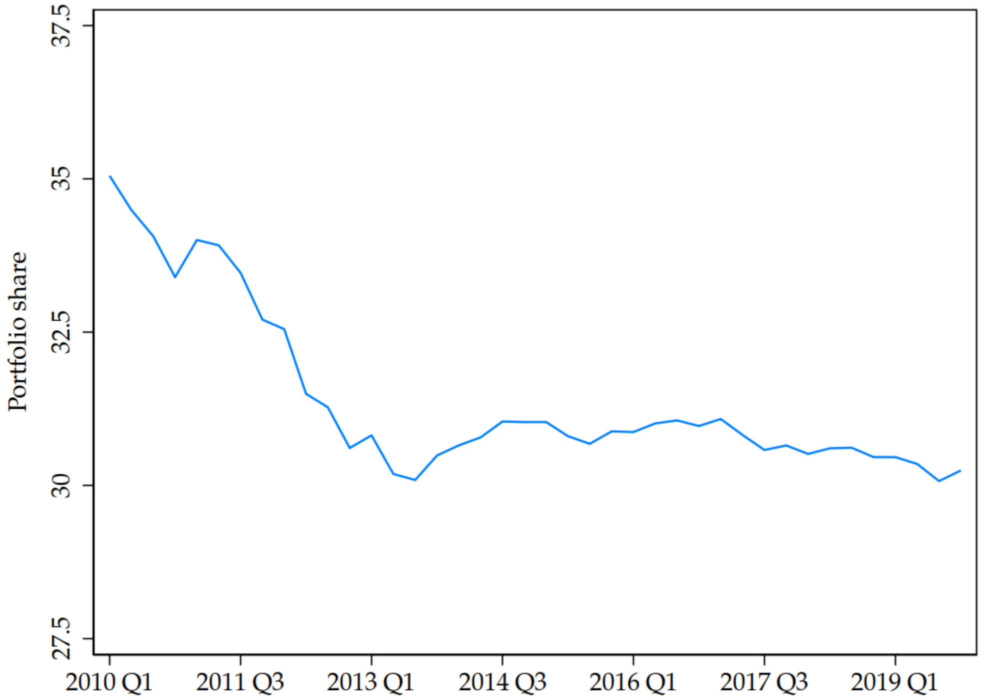


Figure B.3
Insurers' size and asset side composition

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.

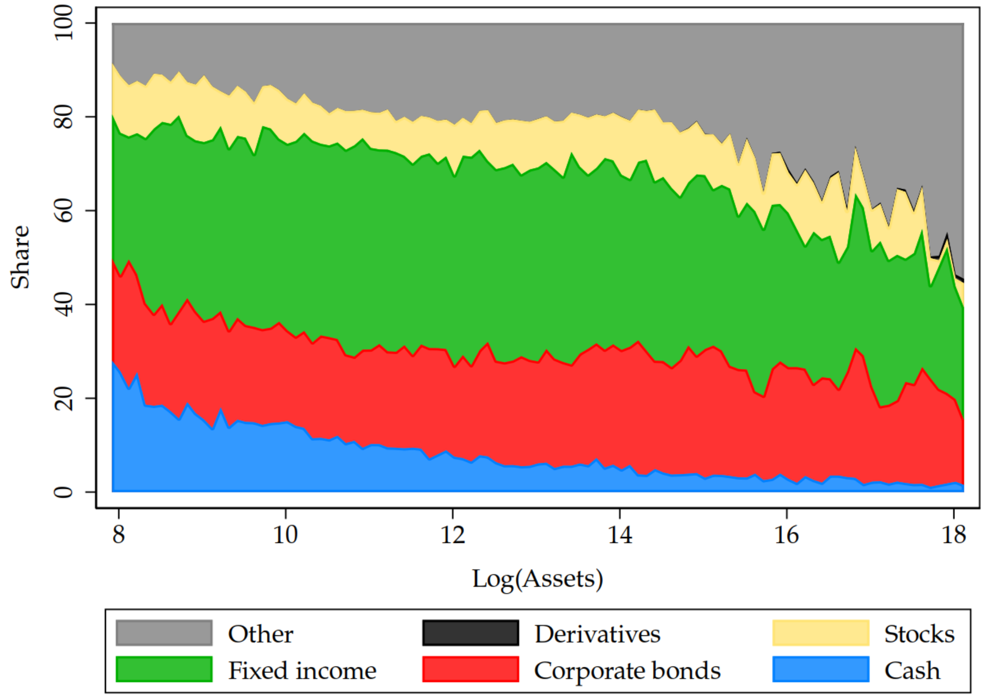


Figure B.4
Insurers' overinvestment in finance bonds across size

This figure plots the estimates for the β coefficients of equation 2 for each of the seven different size buckets scaled by the mean of the dependent variable. The caps represent the 95% confidence intervals. t-statistics are shown in parantheses and based on standard errors that are clustered at the issuer level.

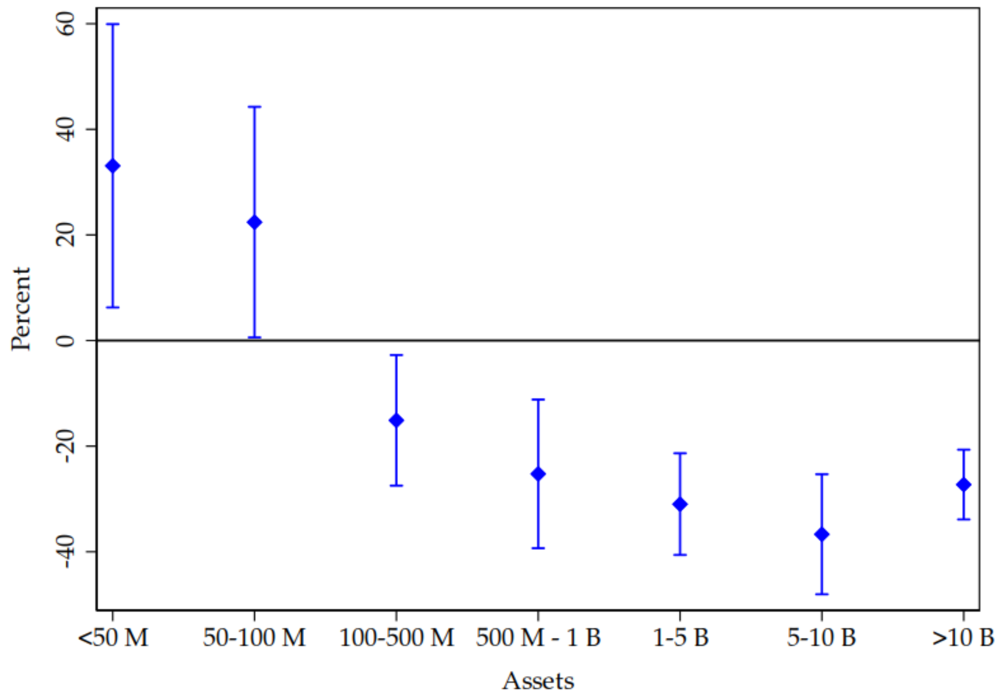


Figure B.5
Robustness: Impact of the 2017 NAIC bond ETF reform on the use of finance bonds

This figure plots the β coefficients of regression 6 for the seven different size buckets scaled by mean of the dependent variable. It replicates the approach from Becker et al. (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.

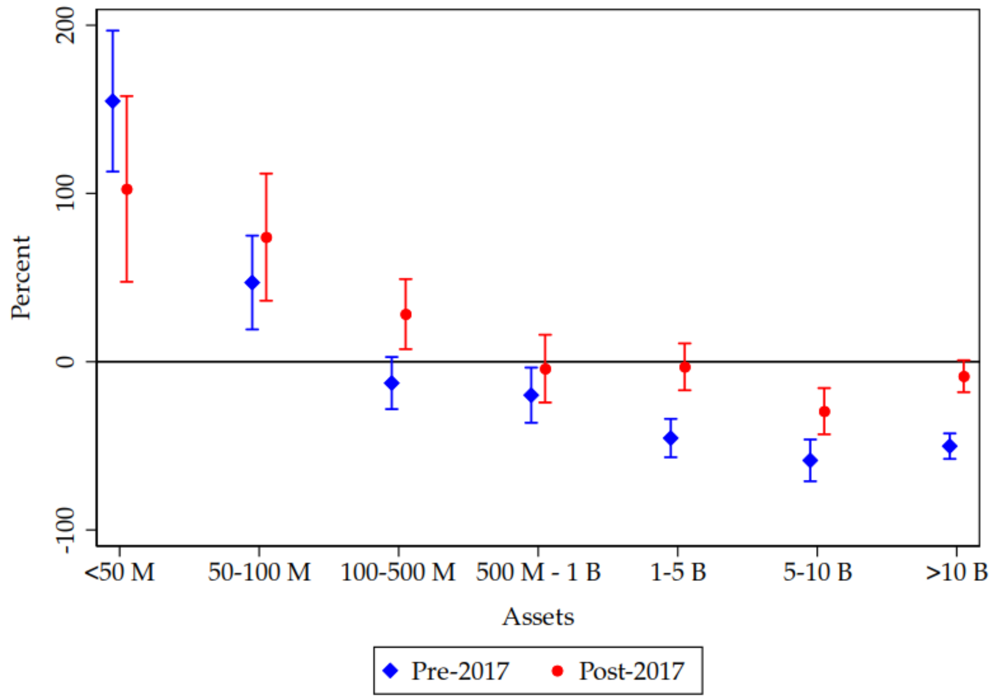


Figure B.6
Correlation of liability side and market risk factor across size

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).

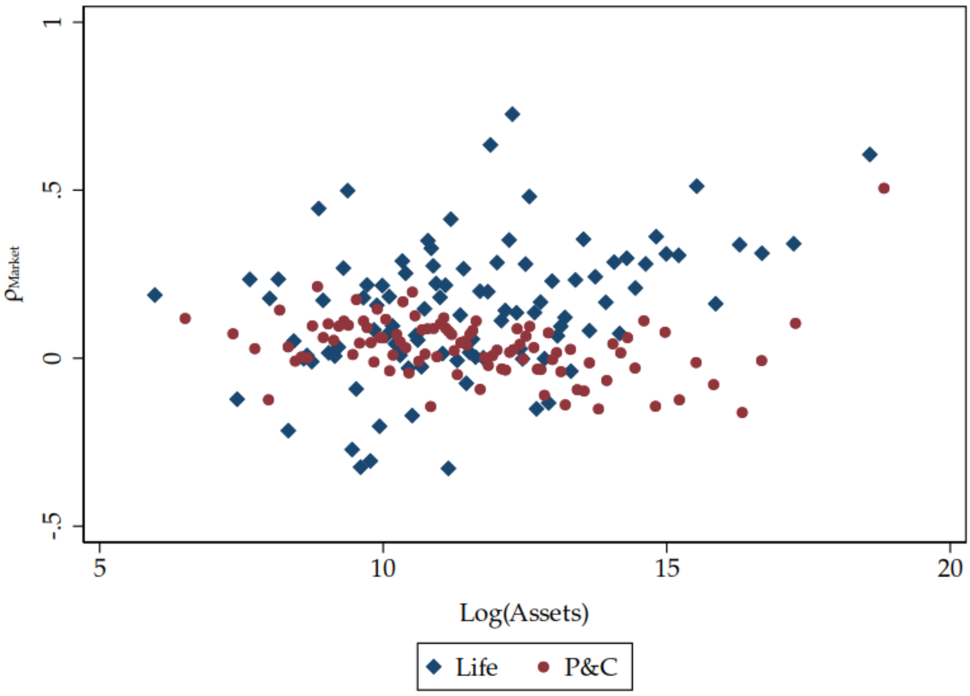
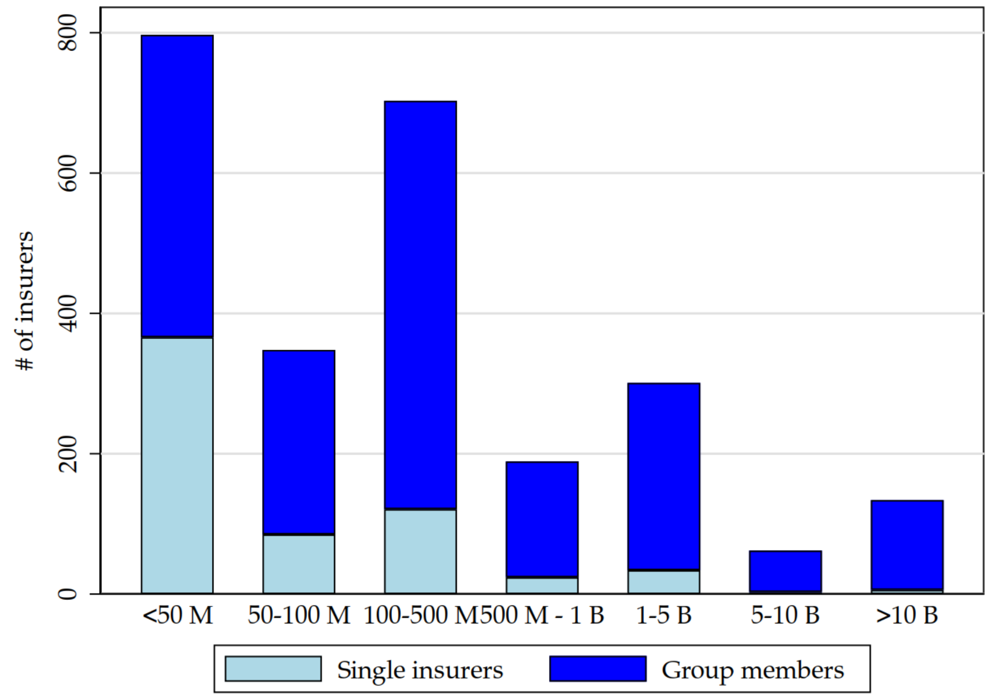
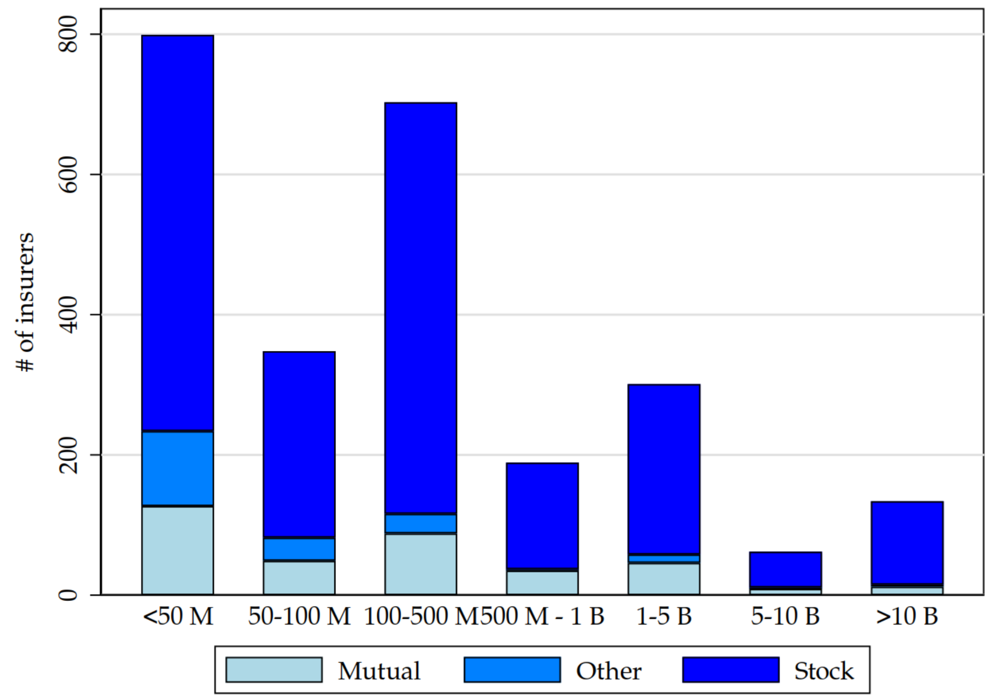


Figure B.7
Group membership and organizational structure

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.



(a) Group membership



(b) Organizational structure

Figure B.8
Systematic value versus NAV

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).

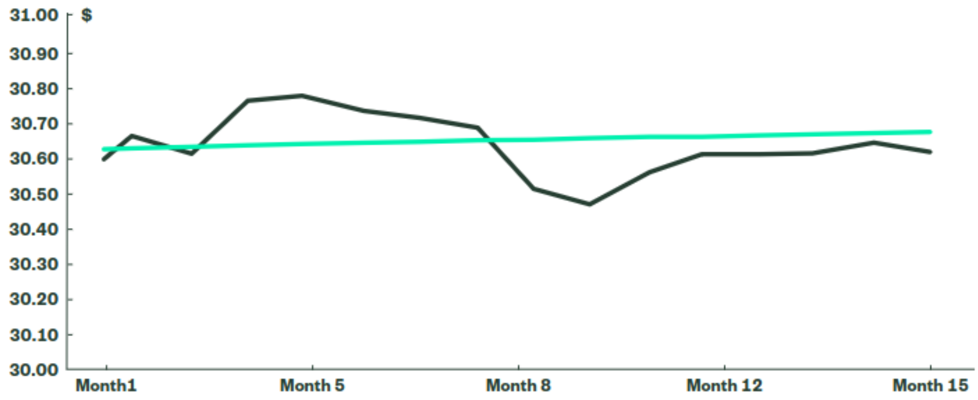
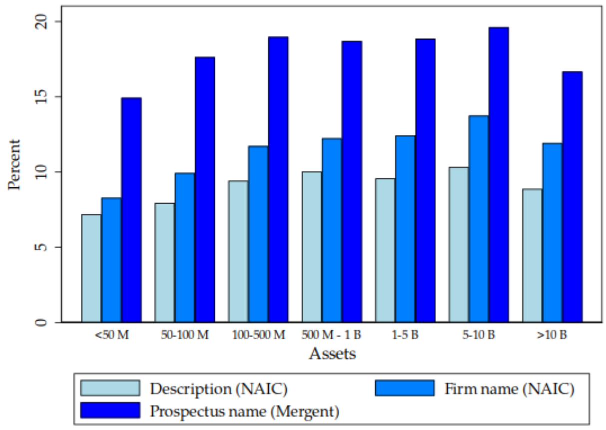
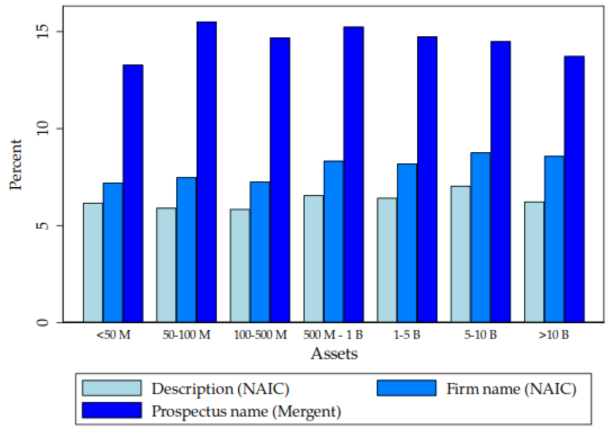


Figure B.9
Robustness: Finance bonds as access to corporate bond markets

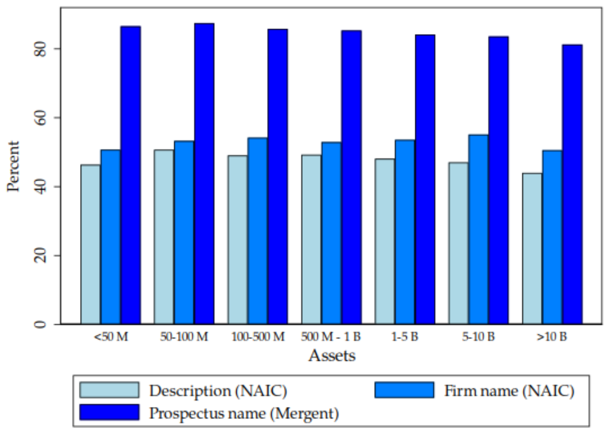
This figure plots the share of acquisitions (lefthand-side figures) and disposals (righthand-side figure) of finance bonds for which the vendor (purchaser) was also the issuer of the traded bond across insurers' size. The share is weighted by the par value traded. Bonds and vendors (purchasers) are matched 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).



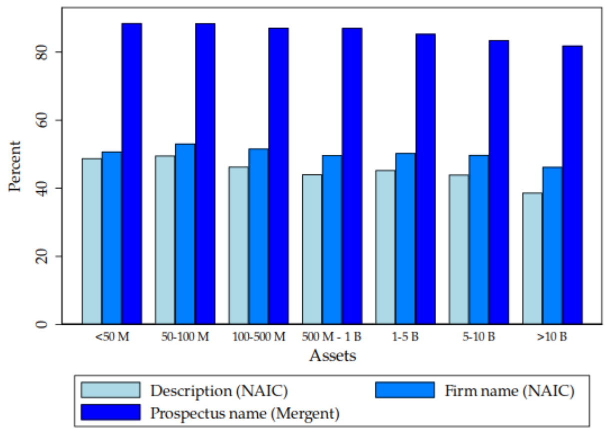
(a) Acquisitions - matching ratio 0.5



(b) Sales - matching ratio 0.5



(c) Acquisitions - matching ratio 0.25



(d) Sales - matching ratio 0.25

C Additional tables

Table C.1
Further information on the sample

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

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

Table C.2
The Size-Investment Relationship in the Fixed Income Portfolio

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*. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	Dependent variable: $\frac{\text{Par value}_{ist}}{\text{Investments}_{it}}$					
Investments$_{it}$:	*Total bonds*$_{it}$		*Total invested assets*$_{it}$		*Total assets*$_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Finance$_s$ × Log(Assets)$_{it}$	-0.954***	-0.954***	-0.469***	-0.469***	-0.527***	-0.527***
	[-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

Table C.3
Summary statistics for the issue-level sample

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.

Panel 1: Issue-level information

	Number of bonds in sample: 17,406						
	Mean	SD	1^{st}	25^{th}	Median	75^{th}	99^{th}
***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	1^{st}	25^{th}	Median	75^{th}	99^{th}
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

Table C.4
Insurers' size, finance bonds, and investments

This table provides estimates of regression equation 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. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	Dependent variable: *Share issue*$_{b;k}$						
Insurers:	$ <50 M	$ 50-100 M	$ 100-500 M	$ 500 M - 1 B	$ 1-5 B	$ 5-10 B	$ >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

Table C.5
Robustness: Insurers' size, finance bonds, and investments

This table provides estimates of regression equation 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. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	Dependent variable: *Share issue*$_{b;k}$					
Specification:	Baseline		+Firm controls & HQ FE		+HQ-Year FE	
Insurers:	\$ <50 M	\$ 50-100 M	\$ <50 M	\$ 50-100 M	\$ <50 M	\$ 50-100 M
	(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

Table C.6
Robustness: Insurers' size, finance bonds, and investments

This table provides estimates of regression equation 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. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

	Dependent variable: *Share issue*$_{bkt}$						
Insurers:	$ <50 M	$ 50-100 M	$ 100-500 M	$ 500 M - 1 B	$ 1-5 B	$ 5-10 B	$ >10 B
	(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

Table C.7
Robustness: Idiosyncratic risk of Finance versus other bonds

This table shows estimates for regression equation 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 $\sigma(\hat{\epsilon})_b$ 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 et al. (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.

	Dependent variable: $\sigma(\hat{\epsilon})_b$						
			Quintiles of *Issuance amount$_b$*				
			1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
	(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

Table C.8
Robustness: Idiosyncratic risk of Finance versus other bonds

This table shows estimates for regression equation 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 $\sigma(\hat{\epsilon})_b$ 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.

	Dependent variable: $\sigma(\hat{\epsilon})_b$						
			Quintiles of *Issuance amount*$_b$				
			1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
	(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

Table C.9
Access to external finance and finance bond investments

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*. t-statistics are shown in parantheses and based on standard errors that are clustered at the insurer level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels.

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

Table C.9 continued.

Panel 2: Organizational structure

	Dependent variable: $Share_{ist}$			
	(1)	(2)	(3)	(4)
Finance$_s$ $\times$ Log(Assets)$_{it}$	-3.240***	-3.178***	-3.137***	-3.128***
	[-11.15]	[-10.58]	[-10.09]	[-10.08]
Finance$_s$ $\times$ Stock$_{it}$	-11.899***	-10.574**	-9.908**	-9.815**
	[-2.95]	[-2.54]	[-2.29]	[-2.27]
Finance$_s$ $\times$ Stock$_{it}$ $\times$ 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

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

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.

	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$_{it}$ $\times$ Log(Assets)$_{it}$	-5.699***		-0.709	
	[-3.00]		[-0.59]	
Low friction$_{it}$		-59.029*		-11.922
		[-1.95]		[-0.72]
Low friction$_{it}$ $\times$ 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

D 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 *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 *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.

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

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.

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.

E 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 B.9, however, shows that the results of Figure 15 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 et al. (2022) and Kubitza (2023) is gratefully acknowledged.