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Historical evidence, such as the global financial crisis of 2007–2009, shows that sectoral asset concentrations can play an important role in insurers' solvency. However, current regulatory frameworks, such as the U.S. risk-based capital (RBC) and the European Union (EU) Solvency II, neglect sectoral asset concentrations when determining capital requirements, potentially underestimating the systematic loss exposure of asset portfolios and reducing incentives to mitigate the corresponding risk.

To assess the solvency risk associated with sectoral asset concentrations, we conduct an empirical analysis based on the statutory filings of 2,708 U.S. insurers over the period from 2009 to 2018. By creating a detailed dataset of their asset holdings, we find that insurers are particularly concentrated in the financial, public, and real estate sectors but also engage in significant asset reallocations, particularly in terms of a declining trend in public sector investments.

To study the potential impact of sectoral asset concentrations on insurers' solvency, we conduct a regression analysis. We use the Z-score to measure solvency and the Herfindahl-Hirschman Index (HHI) to measure insurers' sectoral asset concentration. We find that sectoral asset concentrations can be both beneficial and detrimental to insurers' solvency, depending on the specific sector in which asset portfolios are concentrated. In particular, while asset concentrations in the public sector significantly improve insurers' solvency, asset concentrations in the real estate sector significantly weaken it. One source of concentration risk in the real estate sector can be seen in the existence of speculative, periodically bursting bubbles, one of which triggered the subprime mortgage crisis of 2007–2009.

Our findings can serve as a starting point for revising current regulatory practices regarding risk-adequate capital requirements but also for creating proactive incentives for insurers to mitigate the accumulation of systematic risk associated with sectoral asset concentrations. To foster market discipline, a first step could be to increase public disclosure requirements for insurers regarding their sectoral asset concentrations.

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ABSTRACT

Historical evidence, like the global financial crisis from 2007–2009, highlights that sectoral asset concentrations can play an important role in the solvency of insurers. Yet, current regulatory frameworks, such as the U.S. risk-based capital (RBC) framework, neglect sectoral asset concentrations in the determination of capital requirements, potentially underestimating the asset portfolio's systematic loss exposure and reducing incentives for corresponding risk mitigation. By creating a detailed data sample of U.S. insurers' asset holdings from 2009 to 2018 by means of their statutory filings, we find that insurers concentrate their assets particularly toward the financial, public, and real estate sector and that sectoral asset concentrations toward the public sector are associated with improved solvency, while concentrations toward the real estate sector weaken solvency. Our findings can serve as a starting point to revise current regulatory practices, particularly in terms of creating proactive incentives for insurers to mitigate the accumulation of systematic risk exposures associated with sectoral asset concentrations.

Keywords: Insurance regulation, sectoral asset concentration risk
JEL Classification: G01, G11, G22, G28

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1. Introduction

Insurers invest enormous amounts of premium income, reserves, and equity capital on the capital markets.[1] A concentration of assets in terms of business sectors can generally lead to material loss exposures for financial institutions, as the asset portfolio is increasingly subject to systematic risk exposures. The global financial crisis from 2007 to 2009 provides a prominent example for the financial impact of sectoral asset concentrations on the solvency of insurers. In 2007, AIG and MetLife concentrated 24% and 21%, respectively, of their total assets in the real estate sector, contributing to the material losses for both insurers when the U.S. real estate sector systematically collapsed due to changes in interest rates (McDonald and Paulson, 2015).

Current regulatory frameworks, such as the U.S. risk-based capital (RBC) framework and Solvency II for the European Union (EU), neglect the concentration of assets toward business sectors in the determination of capital requirements for asset concentration risk. In that regard, the capital requirements can underestimate the asset portfolio's systematic loss exposure arising from material and sudden changes in the macroeconomic condition for the invested firms. In the case of a systematic macroeconomic shock, such as changes in interest rates or oil prices, systematic losses materialize that are difficult to manage, and insurers might have insufficient levels of capital to withstand the shocks. Due to the exclusion of the sectoral concentration dimension in the capital requirements, there is less incentive for insurers to mitigate the accumulation of systematic risk exposures associated with the invested sectors.[2] Inadequate regulatory incentives to mitigate sectoral asset concentrations may explain the investment behavior of certain institutions during the global financial crisis, which aggregated assets on a sectoral level to a material extent and is an investment behavior that is still prevalent, according to our analysis.[3] Surprisingly, the literature on sector concentration risk focuses on banks, and the consideration of sectoral asset concentrations in microprudential insurance regulation seems to be driven by anecdotal evidence and supervisory judgment (International Association of Insurance Supervisors [IAIS], 2018b, point 429). In a recent contribution, Che et al. (2021) find empirical evidence that both the hedging motive and underwriting expertise can explain why insurers deviate from a broadly diversified asset portfolio. They underweight equity investments in the insurance industry for hedging reasons, but within their insurance sector investments, they select firms similar to their own. In this paper, we complement Che et al. (2021) in three ways. First, in addition to equity investments, we also include bond and real estate investments in the sector concentration analysis. Second, beyond property-liability insurers, we also include life

1. The International Association of Insurance Supervisors (IAIS) reports a worldwide total asset value of insurers of $44 trillion USD at the end of 2021 (covering more than 90% of global gross written premiums in their survey); refer to IAIS (2022), p. 6.
2. For Solvency II, Delegated Regulation (EU) 2015/35, recital 62, states: "Given that concentration risk is mostly driven by the lack of diversification in issuers to which insurance or reinsurance undertakings are exposed, the market risk concentrations sub-module of the standard formula should be based on the assumption that the geographical or sector concentration of the assets held by the insurance or reinsurance undertaking is not material."
3. See McDonald and Paulson (2015) highlighting the asset concentration on the real estate sector of several financial institutions.

and health insurers, as well as reinsurers. Third, we address the prudential aspects linked to sectoral asset concentrations.

To shed light on these issues, we conduct an empirical assessment based on U.S. insurers' statutory filings over the time period of 2009 to 2018. The analysis aims to provide evidence on how insurers invest their assets regarding sectors, and how sectoral asset concentrations are linked to the solvency of insurers. For the analysis, we proceed in the following way. In Section 2, we briefly summarize the current regulation of asset concentration risk under the U.S. RBC framework and discuss the requirements under Solvency II in Appendix A.1. In Section 3, we create a detailed data sample of U.S. insurers' asset holdings based on their statutory filings and include investment schedules A (real estate), B (mortgage loans on real estate), D (bonds, preferred and common stocks) and BA (other invested assets, especially private equity funds, real estate funds and hedge funds). We then classify the invested assets in terms of sectors by means of an asset-to-asset matching using CUSIP-identifiers and multiple databases (Bloomberg, Refinitiv Eikon, Center for Research in Security Prices [CRSP], and Municipal Securities Rulemaking Board [MSRB]) and use the Global Industry Classification Standard (GICS) as the main sectoral classification system. We find that insurers particularly concentrate their assets toward the financial, public, and real estate sectors over the time period but also engage in material asset re-allocations, particularly in terms of a decreasing trend toward investments in the public sector.

We conduct a regression analysis on a sample of 2,708 U.S. insurers from 2009 to 2018 to study the potential impact of sectoral asset concentrations on insurers' solvency. To measure it, we employ the Z-score, and to measure the insurers' sectoral asset concentration, we employ the Herfindahl-Hirschman-Index (HHI). We find that sectoral asset concentrations can be both beneficial and detrimental to insurers' solvency, depending on the specific sector in which asset portfolios are concentrated. In particular, while asset concentrations toward the public sector significantly improve insurers' solvency, asset concentrations toward the real estate sector significantly weaken it. One source of concentration risk in the real estate sector can be seen in the existence of speculative, periodically bursting bubbles in this sector, one of which triggered the subprime mortgage crisis of 2007–2009.[4]

We acknowledge that it is extremely difficult to accurately identify the effect of the asset allocation choice on solvency in our econometric framework. Yet, despite this drawback, our analysis provides valuable insight that we hope helps to start conversations among regulators about the potential ramifications of sectoral asset concentrations for solvency. The current exclusion of sectoral asset concentrations in the capital requirements in frameworks, such as the U.S. RBC framework, can lead to inaccurate estimates of the systematic loss potential for insurers. We discuss potential ways to revise insurance regulation in that regard, particularly in terms of creating pro-active incentives for insurers to mitigate the accumulation of systematic risk exposures associated with sectoral asset concentrations. A first step could be to increase public disclosure requirements regarding the sectoral asset concentrations to foster market discipline, for instance as part of their own risk and solvency assessments (ORSA). While we focus our analysis on the U.S. RBC framework, we expect our recommendations to

4. Refer to Fabozzi et al. (2020) for recent empirical evidence.

hold for other frameworks as well, such as Solvency II for the EU, which also neglects sectoral asset concentrations in the determination of capital requirements.

Sectoral asset concentrations as a particular dimension of the investment behavior of financial institutions have been studied mainly in banking literature but not in insurance literature. Findings by Beck et al. (2022), Grippa and Gornicka (2016), Düllmann and Masschelein (2007), and Gordy (2003) show that the sectoral concentration in banks' assets can have a substantial impact on their solvency. Regarding property-liability insurers' investment activities, Che et al. (2021) investigate the hedging motive and sector expertise as drivers for sector underweighting and overweighting. The regulatory implications of the investment behavior of insurers have been studied from multiple different perspectives outside the concentration risk angle, for instance, regarding fire sales (e.g. Ellul et al., 2011), reaching for yield behavior (e.g. Becker and Ivashina, 2015) or procyclicality (e.g. Bijlsma and Vermeulen, 2016; Bank of England [BoE], 2014). Evidence on the loss potential associated with sectoral asset concentrations and subsequent regulatory implications are therefore a research gap in the insurance literature. Particularly the lack of publicly available, sufficiently granular investment data of high quality is a major hindering factor to assess whether insurance regulation needs to be revised regarding asset concentration risks (IAIS, 2018b). By analyzing the dynamics of sectoral asset concentrations and their impact on insurers' financial health, we offer a complementary perspective on the complexities of the investment behavior of insurers and the corresponding regulatory treatment.

Our findings also contribute to the literature and discussions around macroprudential insurance regulation, in which sectoral asset concentrations are discussed as a potential source for systemic risk (European Systemic Risk Board [ESRB], 2020; European Insurance and Occupational Pensions Authority [EIOPA], 2019b; International Association of Insurance Supervisors [IAIS], 2018a). In that regard, it is important that microprudential and macroprudential insurance regulation treat sectoral asset concentrations consistently, as a potential misalignment in the approaches could lead to unintended, financially destabilizing effects on the level of individual institutions or the financial system. Asset allocations optimal to minimize the solvency risks of the individual institution are not always optimal from a systemic perspective due to common asset exposures across the institutions (e.g., Wagner, 2010). It is therefore important to first study the microprudential impact of sectoral asset concentrations on the insurers' solvency before introducing macroprudential measures. Our findings can provide the basis for a synchronization of microprudential and macroprudential aims, thus contributing to a more resilient insurance sector.

2. Microprudential Regulation of Sectoral Asset Concentrations

Asset concentration risk comprises an asset portfolio's lack of risk diversification in various dimensions: in terms of individual names (counterparties), business sectors, geographical areas, or asset classes, such as stocks or bonds (Basel Committee on Banking Supervision, 1999). Evidence by McDonald and Paulson (2015) highlights the particularly significant role of sectoral asset concentrations for the substantial losses of several U.S. insurers during the global financial crisis from 2007 to 2009, which concentrated around 20% of their total assets on the real estate sector. In the EU, the EIOPA (2018b) reports almost 40 cases of insurer distress from 1999 to 2016 that were related to concentrated asset portfolios. Sectoral asset concentrations can be associated with material systematic risk exposures. In case of a systematic macroeconomic shock, such as changes in interest rates or oil prices, systematic losses materialize that are difficult to manage for investors, as they cannot be diversified, and insurers may have insufficient levels of capital to withstand the shocks.

Interestingly, current regulatory approaches of frameworks, such as the U.S. RBC framework or Solvency II in the European Union, neglect sectoral asset concentrations in the determination of capital requirements. We focus our discussion of the regulatory treatment of sectoral asset concentrations on the U.S. RBC framework and provide additional insights on corresponding insurance regulation in the EU in Appendix A.1. [5]

The U.S. regulatory insurance framework has different formulas for determining RBC requirements for life, property/casualty (P/C), and health insurers. For the sake of simplicity, we focus the discussion on the case of P/C insurers, which provides a representative example of how sectoral asset concentrations are generally treated in the RBC framework. The total RBC requirement for an insurer at the company action level is given by:

$$RBC = R_0 + \sqrt{R_1^2 + R_2^2 + R_3^2 + R_4^2 + R_5^2 + R_{cat}^2} \qquad (1)$$

where the R-terms denote the risk-based capital for: R_0 - affiliated assets, R_1 - fixed income assets, R_2 - equity assets, R_3 - credit risk, R_4 - reserves underwriting risk, R_5 - premium underwriting risk, and R_{cat} - catastrophe risk.

The capital requirements regarding asset concentrations generally cover only the material idiosyncratic risk exposures to individual names (counterparties) but not the systematic risk exposures to sectors. The capital requirement for asset concentration risk is determined by aggregating all equity and debt instruments issued by single counterparties to find the 10 largest total counterparty exposures. Then, for these 10 large exposures, the asset-specific capital factors are doubled but limited to a maximum factor of 30%. Several specific assets are excluded from a concentration risk charge, for instance, class 1 (low credit risk) and class 6 (high credit risk) bonds, bonds guaranteed by the U.S. government, and affiliated stocks and bonds (NAIC, 2021; 2017).[6] The additional capital charge to the 10 largest fixed-income and equity investments is then added to the corresponding capital requirements R_1 and R_2 in the RBC formula, respectively. Moreover, regarding the fixed income portfolio, there is an additional risk charge depending on the overall number of different names in the bond portfolio, i.e., on the portfolio's granularity (bond size factor adjustment). In that regard, the bond size factors increase or decrease the base bond risk factor conditional on the number of individual names in the portfolio. The RBC for the

5. For an overview of the regulatory treatment of sectoral asset concentrations in the banking sector under Basel III, we refer to ESRB (2020).

6. For bonds, the risk charges range from class 1 bonds with 0.2% to class 5 bonds with 12%. Unaffiliated common stocks have a risk charge of 15% of their book/adjusted carrying value (BACV) (NAIC, 2021; 2017).

fixed-income portfolio is multiplied by a specific diversification factor reflecting a lower loss potential for a more granular fixed-income portfolio.[7]

The asset concentration risk charge is overall designed to mitigate risks associated with insurers overinvesting into a single name and to reflect the potential impact on insurers' solvency capital if the value of the assets associated with a particular name were to significantly decline. The capital framework offers, therefore, an incentive for insurers to spread their investments over many individual names to mitigate the portfolio's idiosyncratic risk exposures but not to spread investments over different sectors to mitigate the portfolio's systematic risk exposures.

The lack of a dedicated regulation of sectoral asset concentrations in the capital requirements might incentivize insurers to concentrate their assets on specific sectors. Becker and Ivashina (2015) show that insurers tend to raise their asset allocations to riskier bonds in a given rating category if it does not require additional solvency capital within that rating category. A similar "search for yield" dynamic might also hold in terms of sectoral concentrations, as insurers might allocate assets toward systematically riskier sectors and would not be charged by additional risk capital. Che et al. (2021) show that insurers' expertise in their underwriting business is also an incentive for asset concentration in the insurance sector, an incentive that is partly offset by hedging deliberations.

According to insurance literature, little is known whether the current regulatory approaches, excluding sectoral asset concentrations in the determination of capital requirements, are appropriately reflecting their potential consequences on insurers' solvency. To shed light on these aspects, the following section assesses empirically the sectoral asset allocation of the U.S. insurance sector and determines its impact on insurers' solvency.

3. Sectoral Asset Concentration Risk in the U.S. Insurance Sector

Since the public financial reports of insurers typically do not contain sufficient granular information to identify the sectoral asset allocations in insurers' investment portfolios, assessing asset concentration risk becomes a challenging task.[8] We overcome the lack of publicly available data by using the statutory filings of U.S. insurers with the National Association of Insurance Commissioners (NAIC) as the basis for our data sample. A detailed description of the steps taken is given in Appendix A.3, and Table 10 in the Appendix shows the data coverage in the sample.

3.1. Assessing Sectoral Asset Concentrations

We include regulatory asset data regarding investment schedules A (real estate), B (mortgage loans on real estate), D (bonds, preferred and common stocks) and BA (other invested assets, especially private equity funds, real estate funds, and hedge

7. A capital factor of 7.8 is implemented to the risk-based capital under R1 for a maximum number of 10 different names in the total debt portfolio, a factor of 1.75 for up to 100 different counterparties, a factor of 1 for up to 200 different counterparties, a factor of 0.8 for up to 500 different counterparties and a factor of 0.75 for more than 500 counterparties (NAIC, 2021).

8. For a similar discussion regarding the banking sector, refer to Beck et al. (2022).

funds) and collect the data from S&P Global Market Intelligence. Since the statutory filings contain the CUSIP numbers of the invested assets, but do not comprise specific information about their corresponding business sectors, we conduct an asset-to-asset CUSIP matching with multiple databases (Bloomberg, Refinitiv Eikon, CRSP, and MSRB) to obtain sectoral classifications of the reported assets. For the CUSIP-based sectoral asset classifications, we use the GICS as the main sectoral classification system. If a GICS classification is not available for a given asset, we aim to get the Thomson Reuters Economic Sector variable. The public administration sector is originally not part of the GICS system, but we treat it as a separate sector to comprise the typically large investments of insurers in public debt instruments and to get an economic perspective of the corresponding effects on the insurers' solvency.

Regarding an asset's value as the main determinant for a portfolio's sectoral concentration, we follow the NAIC in its market analyses and use the reported book/adjusted carrying value (BACV) of the asset. The BACV is an accounting-based measure that considers the asset's book value adjusted by the insurer for certain economic factors (e.g., market developments) to reflect the asset's actual economic value. The BACV is the essential determinant to calculate the insurers' asset-related capital requirements in the U.S. RBC framework.

We measure the insurers' sectoral asset concentration by means of the HHI. The HHI as a concentration measure has been frequently used in the literature, for instance by Shim (2017a, 2017b) and Acharya et al. (2006). The insurers' sectoral HHI per year is determined by the sum of the squared ratios of the aggregated asset values in terms of the BACV allocated to a specific sector to the portfolio's total value of assets. Thereby, a higher HHI value indicates the asset portfolio to be stronger concentrated, whereas a lower HHI value indicates the asset portfolio to be more diversified, i.e., less concentrated. The insurer sample for the analysis consists of 2,708 individual U.S. entities registered by a company code with the NAIC over the time period from 2009-2018 and is described in more detail in Section 3.4, as it is the basis for the subsequent regression analysis as well.

3.2 Empirical Evidence on Sectoral Asset Concentrations

For descriptive purposes, Table 1 shows the sectoral concentrations of the total assets reported by all insurers in the sample in 2018. In general, insurers materially spread their investments by holding assets from every sector as classified by the GICS. However, some sectoral imbalances are apparent. The largest allocation refers to investments in the financial sector with 33% of the total assets, for which affiliated investments play an important role, especially in the context of common stock investments in parent, subsidiaries, and affiliates.[9] In that regard, it seems like insurers tend to invest largely in each other, suggesting a relatively strong financial interconnection across entities in the insurance sector. The second highest sectoral asset concentration is in the real estate sector with a fraction of 13%. The allocation to the real estate sector is about one-third less than the reported figures of 20% for certain insurers during the global financial crisis between 2007 and 2009, as highlighted by McDonald and Paulson (2015). The third highest sectoral asset concentration is in the public sector

9. Corresponding assets with reported line numbers 9100001-9199999 in the statutory filings.

with a fraction of 10% (comprising sovereign and municipal debt instruments). The insurers show moderate concentration levels in the industrials, utilities, health care, and consumer staples sectors (around 4% to 6%), and minor investment levels below 3% in the remaining GICS sectors.

Table 1: Sectoral Asset Concentrations of the U.S. Insurance Sample in 2018

Sector	Year	Ratio	Average (2009-2018)
Financials	2018	0.33	0.32
Real Estate	2018	0.13	0.07
Public Administration	2018	0.10	0.13
Industrials	2018	0.06	0.06
Utilities	2018	0.05	0.05
Health Care	2018	0.04	0.03
Consumer Staples	2018	0.04	0.04
Energy	2018	0.03	0.04
Information Technology	2018	0.03	0.02
Consumer Discretionary	2018	0.02	0.02
Materials	2018	0.02	0.02
Communication Services	2018	0.02	0.02
Residual Sectors (each)	2018	< 0.01	< 0.01
Unclassified Assets	2018	0.12	0.16

Table 1 shows the sectoral asset concentrations of the entire sample of 2,708 U.S. insurers in 2018, as determined by the book/adjusted carrying value (BACV) of all sector-specific assets aggregated by all insurers in the sample divided by the aggregated BACV of all reported assets in 2018. Investment data comprises schedules A, B, D, and BA from the insurers' statutory filings with the NAIC. We follow McDonald and Paulson (2015) and include investments from Schedule A (direct property) and Schedule B (mortgage loans on real estate) under the real estate sector. *Own Table*.

The column "Average" in Table 1 provides the average values over the entire sample period from 2009 to 2018. Interestingly, for most sectors, insurers seem to follow a stable asset allocation, as the most recent observations in 2018 are close to their corresponding long-term average values from 2009 to 2018. A reallocation of assets over time appears to have taken place in the real estate sector, showing an increase from 7% (long-term average) to 13% in 2018. In contrast, the asset allocations to the public sector show a decrease from 13% (long-term average) to 10% in 2018. This could be in line with the general low-interest rate environment over a material time period of the entire time window studied, placing insurers under pressure to shift assets into other sectors to generate sufficient investment yields. Table 11 in Appendix A.3 shows, as extension to Table 1, the year-by-year breakdown of the sectoral asset allocations, underlining that insurers pursue stable asset allocation levels over time for most sectors, and major re-allocations appearing only in the financials, real estate, and public sector.

The differentiation of the invested asset types in the five most important sectors in Table 2 underlines the generally conservative investment behavior of insurers regarding the seniority of the assets. The focus of the invested assets lies on fixed-income instruments in terms of bonds, followed by equity investments, particularly in the financial sector. Investments in the real estate sector show a different allocation across asset types. Insurers' large investments in mortgage loans comprise 72% of the sectoral investments related to real estate, followed by bonds issued by firms in the real estate sector (18%). Insurers' direct property holdings amount to 4% of the investments in the real estate sector, and the long-term assets, based on a look-through approach by means of the assets' reported CUSIP and line numbers, amount to 5%. Comparing the recent allocations in 2018 with the long-term average values over 2009–2018, we see only limited changes per asset type for most sectors, except for the real estate sector, which shows a material shift from bond-related investments (18% in 2018, 62% long-term average) to mortgage loans (72% in 2018, 25% long-term average) over time.

Table 2: Invested Asset Types in 2018

Sector	Allocation	Bonds	Stocks	Long-Term	Direct Property	Mortgage Loans
Financials	0.33	0.73	0.24	0.03	-	-
	(0.32)	(0.78)	(0.21)	(0.01)		
Real Estate	0.13	0.18	0.01	0.05	0.04	0.72
	(0.07)	(0.62)	(0.01)	(0.06)	(0.06)	(0.25)
Public Admin.	0.10	1.00	-	-	-	-
	(0.13)	(1.00)				
Industrials	0.06	0.75	0.11	0.14	-	-
	(0.06)	(0.78)	(0.10)	(0.12)		
Utilities	0.05	0.98	0.02	-	-	-
	(0.05)	(0.98)	(0.02)			

Table 2 shows the asset types of the insurers' investments in the five most important sectors in 2018. In parentheses are the long-term average values for the period 2009 to 2018. *Own Table*.

To get a more granular perspective on the investment behavior of individual insurers, Table 3 shows the insurer-specific values of the sectoral HHI averaged over all insurers in the sample, and the corresponding standard deviation per year. Individual insurers, on average, tend to concentrate their assets to the sectors they invest in, with an average HHI between 0.31 and 0.36 from 2009 to 2018.[10] While the sectoral asset concentrations of insurers seem to be overall relatively stable over time due to its narrow range between 0.31 and 0.36. Figure 1 shows a trend toward lower levels of sectoral asset concentrations until 2014/2015 by means of declining levels of the HHI, and then slightly increasing levels of the HHI onwards indicating higher levels of sectoral asset concentrations. The decreasing trend of the sectoral HHI can be explained in the data by decreasing asset concentrations to the public and real estate sector while the allocations to the financial sector only moderately changed, allowing for more sectoral diversification in the asset portfolios (Table 11, Appendix A.3). After 2015, the slightly increasing trend in the sectoral HHI is mainly related to an increase in the sectoral asset allocations to the financial and real estate sector, indicating less sectoral asset diversification.

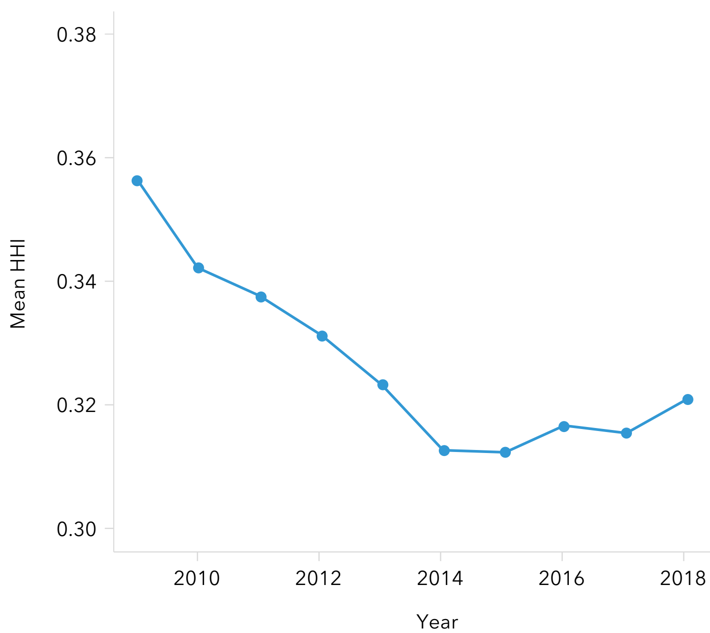
10. There are typically no strict HHI threshold levels defined where the measure is considered to indicate a strong concentration level. Regarding the market competition literature, a field that relies strongly on the use of the HHI to evaluate the degree of market competition, an HHI of more than 0.25 is typically considered to indicate a highly concentrated market (U.S. Department of Justice and Federal Trade Commission, 2010).

Table 3: Sectoral Asset HHI

Year	Mean HHI	SD HHI
2009	0.36	0.20
2010	0.34	0.19
2011	0.34	0.19
2012	0.33	0.19
2013	0.32	0.19
2014	0.31	0.17
2015	0.31	0.17
2016	0.32	0.18
2017	0.32	0.17
2018	0.32	0.17

Table 3 shows the mean and standard deviation of all insurer-specific sectoral Herfindahl-Hirschman-Index (HHI) values in the sample from 2009 to 2018. Figure 1 shows the time series of the average sectoral HHI over time. *Own Table and Figure*.

Figure 1: Time Series of the Sectoral Asset HHI



Moreover, the relatively stable annual standard deviation of the HHI of around 0.2 indicates a material and stable dispersion of how individual insurers concentrate their investments regarding sectors relative to each other (Table 3). Some insurers show very low levels of sectoral asset concentrations while others show extremely high levels of sectoral asset concentrations, ranging from 0.1 to 1.0 (also refer to the sample's summary statistics in Table 4), suggesting insurers seem to have different perspectives on the appropriate levels of sectoral asset concentrations in their portfolios. This finding is interesting, as the strong sectoral asset allocations, particularly to financial, public, and real estate sectors as shown in Table 1, are discussed in the literature to cause severe financial contagion risks for insurers in case of a systematic shock in these sectors. Düllmann and Masschelein (2007) show that sector concentrations in banks' credit portfolios can increase the required economic capital to back up losses by more than 37%. Findings by the IMF (2018), Chen et al. (2013), and Allen and Carletti (2006) underline the substantial spillover risk of shocks from banks to insurers that can deplete insurers' solvency. In addition, Acharya et al. (2014) show a reinforcing link between sovereign and bank credit risk in case of a banking shock, which can threaten insurers' financial condition as a double-hit scenario.

3.3 Regression Model

We aim to find empirical evidence on the implications of sectoral asset concentrations on insurers' solvency by means of a regression analysis. Sectoral asset concentrations associated with higher systematic risk exposures could be expected to harm insurers' solvency, in line with theoretical expectations on the effects of reduced diversification benefits (e.g., Düllmann and Masschelein, 2007). However, also a positive effect of sectoral asset concentrations on insurers' solvency can be expected, if sectoral asset concentrations are associated with information advantages and better risk monitoring that could lead to excess asset returns (Acharya et al., 2006).

To assess the potential impact of sectoral asset concentration on insurers' solvency, the following multivariate regression model is studied:

$$Y_{i,t} = \beta_0 + \beta_1 \, HHI_{i,t-1} + \beta_{CV} \, CV_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

$Y_{i,t}$ is insurer i's Z-score in year t; $HHI_{i,t-1}$ is the sectoral HHI of insurer i in the previous year t-1; and $CV_{i,t-1}$ is a vector of insurer characteristics in year t-1 to control for other factors that could affect the insurers' solvency. $\varepsilon_{i,t}$ denotes the error term. The description of variables is given in Appendix A.4.

As the dependent variable (Y) to measure the insurers' solvency, the Z-score is employed, which is an accounting-based measure frequently used in the insurance and banking literature to determine an institution's solvency (e.g., Pasioura and Gaganis, 2013; Shim, 2017b, for the insurance literature; Köhler, 2015; Laeven and Levine, 2009, for the banking literature). The Z-score increases with lower levels of volatility of the insurer's return on assets as well as improvements in the insurer's profitability and capital position to withstand shocks and decreases with higher levels of volatility in the asset returns as well as with lower levels of profitability and less capital to withstand shocks. A higher Z-score therefore indicates a better solvency of an insurer, and we follow Shim (2017b) by defining the measure as:

$$Z - score_{i,t} = \frac{RoA_{i,t} + CAR_{i,t}}{SD(RoA)_{i,t}} \tag{3}$$

$Z - Score_{i,t}$ the Z-score of insurer i in year t; $RoA_{i,t}$ denotes the return on assets of insurer i in year t, which is calculated as net income before taxes (EBT) divided by total net assets; and $CAR_{i,t}$ denotes the capital-to-asset ratio of insurer i in year t, which is calculated as the ratio of total equity (i.e., insurance surplus) to total net assets. $SD(RoA)_{i,t}$ denotes the standard deviation of the return on assets (RoA), which is determined in two different specifications to increase the robustness of the analysis: (i) on a three-year rolling window and (ii) over the entire time series of observations per insurer.

There are several alternatives to the Z-score that could be used to measure solvency risk. Kim et al. (2023) use the RBC ratio, i.e., total adjusted capital divided by the RBC. In a robustness check, we employ the RBC ratio and find similar results as in the Z-score analysis. Beck et al. (2022), in their analysis of sector concentration risk in banks, use the "Distance-to-Default" risk measure, going back to Merton (1974). It "measures the difference between the asset value of the bank and the face value of its debt, scaled by the standard deviation of the bank's asset value" (Beck et al., 2022, p. 1721). Due to the lack of face values of insurers' technical reserves as the main component of their liabilities, "Distance-to-Default" does not seem to be an appropriate risk measure in the insurance context, and we are not aware of any research in the insurance context using it. Beck et al. (2022) also apply the Marginal Expected Shortfall, as proposed by Acharya et al. (2017), as a (systemic) risk measure. To calculate it, one would need the returns of the insurers' publicly traded stocks, which are not available for our analysis, as we focus on data at the unconsolidated entity level. The use of "Expected Policyholder Deficit," "Value-at-Risk," or "Expected Shortfall" as solvency risk measures (refer to Eling et al., 2009; Wagner, 2014) would require parameters to simulate asset performance and insurance business risk or the time series of stock returns that reflect both asset and liability risk. Again, the lack of data availability is an obstacle to using these risk measures in our framework. Moreover, Sharma, Jadi, and Ward (2018) use insurers' rating transitions to measure changes in solvency risk. Leverty and Grace (2018) employ "hazard analysis" (Shumway, 2001) to analyze the relationship between the timing of regulatory actions indicating insurer failure and the election of insurance commissioners in the U.S. In their analysis, the taking or not taking of regulatory actions is mapped by a binary variable. This approach is appropriate for studying insurer failure situations, where firms that do not fail are counted as "survivors." With respect to the influence of sector concentration on insurers' solvency, we prefer the Z-score to the observation of the binary failure/non-failure event or the observation of rating changes because the Z-score captures the continuous transition from a healthy to a financially distressed firm. Moreover, Beck et al. (2022) show no significant differences when assessing the potential impact of sectoral asset concentrations on a financial institution's solvency for accounting- or stock return-based solvency measures.

The main variable of interest is the sectoral asset concentration, which we measure by means of the HHI. The HHI has been frequently used in the literature to measure risk concentrations (e.g., Bayar et al., 2018; Shim, 2017a, 2017b; Berry-Stölzle et al., 2012; Acharya et al., 2006) and is also a frequently used prudential measure in banking regulation (Basel Committee on Banking Supervision, 2019).[11] The insurer-specific HHI in year t is determined by the sum of the squared ratios of the aggregated asset values in terms of the BACV allocated to a specific sector to the portfolio's total value of assets. A higher value of the HHI indicates a stronger sectoral concentration of the asset portfolio.

11. Basel Committee on Banking Supervision (2019): "Regarding indices and thresholds for the assessment and monitoring of concentration risk, about half of supervisors use the Herfindahl-Hirschman index (HHI)…," p. 15.

Several insurer-specific control variables (CVs) are employed in the model. The sectoral HHI is an aggregated measure and is informative of the overall impact of sectoral asset concentrations on insurers' solvency. Since economic sectors typically show systematic differences in their financial performance influencing insurers' solvency, and individual insurers might overweight or underweight their asset allocations to specific sectors for strategic reasons, e.g., due to informational advantages as suggested by Che et al. (2021), we assess by means of indicator variables to which of the invested sectors the asset portfolio was concentrated in the given year (maximum of the percentage of sector-specific assets to total assets). We control for the insurers' size since larger institutions tend to be more financially stable because their larger asset and underwriting risk pools benefit more from risk diversification effects (Shim 2017b; Liebenberg and Sommer, 2008). However, large insurers may also be incentivized to engage in excessive risk taking, as they may be considered "too big to fail," which could reduce their solvency (Financial Stability Oversight Council [FSOC], 2013). We further control for the asset risk in the insurers' portfolios to the fraction of fixed-income assets since a higher seniority of assets raises the portfolios' resilience against financial shocks (Shim 2017b). As the leverage of a financial institution can influence its potential to withstand financial shocks and thereby influence its solvency, we control for the insurers' leverage (Shim, 2017b; Chen and Wong, 2004; Carson and Hoyt, 1995). Moreover, as insurers also engage in non-insurance related activities, such as securities lending or derivatives trading that can affect their solvency (e.g., IAIS, 2019), we control for the engagement in non-insurance related activities (Bierth et al., 2015; Weiß and Mühlnickel, 2014). We also control for the level of underwriting risk since particularly unexpected underwriting-related losses can be negatively associated with the financial performance of insurers (Che et al., 2021). Since reinsurance is a typical risk mitigation tool of insurers to protect the ceding company against unexpected underwriting losses and, therefore, influences the insurers' solvency, we include the reinsurance ratio in the given year (Che et al., 2021). Moreover, following Che et al. (2021), we include the insurers' age as an approximation for their investment experience to account for the potential of more experienced insurers to generate abnormal asset returns due to sector-specific information advantages. To account for systematic differences in the corporate and ownership structure, we control by means of indicator variables whether the insurer is part of a group or is a stock/mutual insurer, respectively. In addition, we control for time-fixed effects on an annual level, and the model is estimated by means of clustered standard errors on the insurer level to account for serial correlation of unobserved factors in the insurer-specific data. Since insurers are typically long-term investors with relatively stable strategic asset allocations (refer to Table 1), the within-firm variation of the sectoral HHI measure is generally limited, and insurer-fixed effects would absorb most of the variation in the data. We, therefore, follow Che et al. (2021), Eling and Jia (2018), van Oordt and Zhou (2018), as well as Liebenberg and Sommer (2008), and estimate the main model without firm-fixed effects. In the robustness checks, we, however, report the findings implementing insurer-fixed effects. Moreover, to mitigate reverse causality, i.e., a potential influence of the insurers' solvency as a dependent variable on the sectoral asset allocation as an explanatory variable, we lag all explanatory variables by one year. An overview of the variables is provided in Appendix A.4 (Table 12).

3.4 Descriptive Statistics of the Regression Sample

The sample of insurers is based on U.S. entities registered by a company code with the NAIC. To mitigate selection and survivorship bias, the sample includes operating and non-operating insurers. The sectoral asset concentrations, as described in Section 3.1, are based on reported asset data regarding the investment schedules A (real estate), B (mortgage loans on real estate), D (bonds, preferred and common stocks), and BA (other invested assets, especially private equity funds, real estate funds, and hedge funds), collected from the insurers' statutory filings through S&P Global Market Intelligence over the time period from 2009 to 2018. The 10-year data range covers the insurers' investment behavior through different market cycles, including times of economic growth, and also, important from a prudential perspective, times of economic stress, such as the aftermath of the global financial crisis (2007–2008) and the low-interest rate environment. Appendix A.3 provides further details on the matching procedure regarding the assets' sectoral classifications.

Data to determine the Z-score, as well as the control variables, has been collected through S&P Global Market Intelligence. Data has been cleaned for negative values regarding total net assets, premiums written, total liabilities, and insurance reserves, materially reducing the number of available observations. Moreover, data has been cleaned for missing observations regarding the variables of the regression model, and observations where the determined reinsurance ratio was higher than 100% have also been removed, as well as insurers that are neither mutual nor stock insurers.

The final sample consists of 2,708 insurers, with 77% P/C insurers and 23% life and health (L&H) insurers. Among these insurers, stock insurers are the majority (80%), and most insurers are part of a group (70%). Table 4 provides a descriptive overview of the variables included in the analysis, offering insights into the characteristics of the sample of insurers for the regression analysis. Regarding the dependent variables, the Z-score is estimated either based on a three-year rolling window of observations on the insurers' return on assets or on the insurers' full time series of observations on the return on assets (Z-score [TS]). The sample shows a wide range of solvency levels of the insurers in the sample. The minimum value depicted in logarithmic terms is around -2.0, the maximum around 7, with a mean value around 3. The values are in line with the insurance literature, e.g., Pasiouras and Gaganis (2013).

The main variable of interest, the HHI based on the insurers' sectoral asset allocation, reflects the degree of sectoral asset concentration. The mean HHI value of 0.3 suggests material sectoral concentration levels, while the standard deviation of 0.2 illustrates material dispersion in the sectoral asset concentrations across insurers. The individual HHI figures of the insurers range from 0.1 to 1.0, indicating a wide spectrum of diversified to highly concentrated portfolios as regards the sectoral asset allocation. Regarding the insurers' size, the sample includes very large insurers but also very small entities and is skewed to the large insurers. The variable "Asset Risk" as the ratio of bond-related investments to total investments to capture the portfolios' level of asset risk underlines the relatively conservative investment behavior of insurers as mainly bond investors. On average, around 80% of the investments are made through bonds. Leverage, linked to the financial buffer of insurers to withstand potential shocks, is at a moderate level on average. Moreover, the average insurer engages only moderately in non-insurance activities, with an average ratio of total liabilities to policyholder surplus of 2.8. The distribution of the variables underwriting risk, reinsurance, and age shows material cross-sectional variation among insurers and is in line with the literature (Che et al., 2021).

Table 4: Descriptive Statistics of the Sample

Variable	Mean	SD	Min	Max
Z-score	3.4	1.1	- 0.4	7.1
Z-score (TS)	2.7	0.8	- 1.7	5.2
ACL RBC Ratio	6.9	0.8	2.7	11.8
HHI	0.3	0.2	0.1	1.0
Size	11.9	2.3	4.4	19.8
Asset Risk	0.8	0.2	0.0	1.0
Leverage	1.0	1.2	0.0	13.6
Non-Insurance Activities	2.8	4.4	0.0	25.7
Underwriting Risk	0.1	0.5	0.0	9.9
Reinsurance	0.3	0.3	0	1.0
Age	50.2	40.7	1.0	266.0
Group (Yes/No)	0.7	0.4	0	1.0
Ownership (Stock/Mutual)	0.2	0.4	0	1.0

Table 4 shows the descriptive statistics of the sample of 2,708 insurers for the regression analysis over the time period from 2009-2018, consisting of an unbalanced panel with a total of 21,238 firm-year observations. Definitions and data sources are given in Appendix A.4. Z-score denotes the Z-score determined by means of a three-year rolling window over the insurers' RoA observations, whereas Z-score (TS) denotes the Z-score determined by the insurers' full time series of RoA observations. Both Z-scores and size (total net assets) are in logarithmic terms. HHI is the Herfindahl-Hirschman-Index (HHI) of the sectoral asset concentrations. The RBC ratio is at an authorized control level (ACL) and reported in logarithmic terms.

3.5 Main Results of the Regression Analysis

Table 5 provides the results of the baseline regression analysis, revealing insights into the relationship between the dependent variables as indicators of insurers' solvency and the sectoral asset concentrations as the main variable of interest. The sectoral HHI shows a statistically significant positive relationship with the insurers' solvency in both estimations of the Z-score (β = 0.484 and β = 0.311), indicating that a higher sectoral asset concentration is, on average, associated with a higher solvency for the insurer as determined by the Z-score. The relationship is economically meaningful, as an increase in the sectoral asset concentration in terms of the HHI by one standard deviation leads, on average, to an increase in insurers solvency by approximately 9.6%.[12]

12. With a beta of 0.484, it approximately follows for an increase by one standard deviation in the sectoral HHI (SD = 0.2): 48% * 0.2 = 9.6%.

Table 5: Baseline Regression Results

	Dependent Variable	
	Z-score	Z-score (TS)
HHI	0.484***	0.311***
	p = 0.000	p = 0.000
Size	0.057***	0.042***
	p = 0.000	p = 0.000
Asset Risk	0.381***	0.241***
	p = 0.000	p = 0.000
Leverage	- 0.170***	- 0.150***
	p = 0.000	p = 0.000
Non-Insurance Activities	- 0.041***	- 0.046***
	p = 0.000	p = 0.000
Underwriting Risk	- 0.156***	- 0.117***
	p = 0.000	p = 0.000
Reinsurance	0.001	0.071
	p = 0.990	p = 0.156
Age	0.113***	0.131***
	p = 0.000	p = 0.000
Group	0.085**	0.043
	p = 0.030	p = 0.250
Ownership	- 0.070*	- 0.120***
	p = 0.090	p = 0.002
Year Fixed Effects	Y	Y
Firm Clustered SE	Y	Y
Observations	21,038	20,949
R2	0.113	0.173
Adj. R2	0.113	0.173

Note: *p<0.1; **p<0.05; ***p<0.01
Table 5 shows the results of the OLS panel regression on the model given by Equation (2) from 2009 to 2018. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year, and the dependent variables, the size variable, and the age variable are in logarithmic terms. All panel regressions are estimated with year-fixed effects and clustered standard errors at the insurer level. Model (1) refers to the Z-score estimated by means of a three-year rolling window over the RoA observations, and Model (2) refers to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

Given the expectation that a higher sectoral asset concentration typically leads to higher systematic risk exposures in the portfolio, the finding of a positive relationship indicating improvements in the insurers' solvency is surprising. It can be explained by the insurers' typical investment behavior and the fact that the HHI is an aggregated concentration measure that does not depict the interaction of the sectoral asset allocations influencing the volatility of the asset portfolio's overall returns. Insurers tend to concentrate their assets in the public sector, which is considered to provide relatively safe asset returns in terms of the high-quality sovereign bonds in which insurers usually invest. A higher sectoral HHI is, therefore, largely associated with an increase in the asset allocation toward the public sector. Due to the low systematic risk exposure of assets related to the public sector, the asset portfolio's total systematic risk exposure reduces, which improves the solvency of an insurer. Moreover, a similar rationale holds for the insurers' asset allocations to the utilities sector, which is usually providing stable asset returns due to its stable economic activity of providing electric, gas, or water services essential for the real economy and society. Also, given that insurance-related assets are typically less risky than banking-related assets, an increase in the sectoral asset concentration toward the financial sector can also improve the asset portfolio's overall risk exposure. The positive relationship between the sectoral asset concentration and the insurers' solvency suggested by the regression analysis is further supported by findings in the literature, as Beck et al. (2022) find a positive impact of a bank's sectoral asset concentration on a bank's default risk, consistent with the financially stabilizing benefits stemming from better risk management of concentrated asset portfolios due to informational advantages or risk monitoring (Acharya et al., 2006).

The baseline regression findings suggest that from an aggregated perspective in terms of the sectoral HHI measure, higher levels of sectoral asset concentrations can be positive for the solvency of an insurer. However, since there are typically cross-sectional differences in the financial performance of sectors, and individual insurers might overweight or underweight their investments to specific sectors for strategic reasons (e.g., informational advantages as suggested by Che et al., 2021), we run a complementary regression analysis to focus on the specific sectors to which insurers concentrate their asset portfolios. In this regard, insurers in the sample overall show a maximum allocation of their assets to the financial, public administration, industrials, real estate, energy, consumer staples, and materials sectors. We add an indicator variable to the regression model, indicating in which of these sectors the asset portfolio is concentrated in the given year.

Table 6 provides the results of the baseline regression analysis with an indication on which sector the asset portfolio is concentrated. Asset portfolios concentrated in the public sector are, on average, associated with a higher solvency of the insurer (β = 0.104 and β = 0.144), which is in line with the typically relatively safe asset returns related to government bonds. Interestingly, the sectoral asset concentration toward the real estate sector is strongly negatively affecting insurers' solvency (β = - 0.355 and β = - 0.278). The result becomes plausible when considering the recent empirical findings of Fabozzi et al. (2020), who provide evidence for the existence of speculative, periodically bursting bubbles in the real estate sector. Their sample period for the U.S. market is from 1997-2015, which covers most years of our sample period 2009-2018. Our sample period includes years of undervaluation (2009-2014) and years of overvaluation (2015-2018) in the real estate sector (UBS, 2023, p. 9). Thus, we see a persistent bubble risk also after the global financial crisis from 2007-2009, which was associated with substantial losses for financial institutions that had material asset concentrations in the real estate sector (McDonald and Paulson, 2015).

Sectoral asset concentrations toward the financial, energy, and consumer staples sectors tend to improve insurers' solvency, since the Z-score estimated on the full time series of the RoA data (Model 2) shows a weakly significant positive effect. This effect is not evident for a Z-score estimated by means of a three-year rolling window over the RoA (Model 1). The other control variables in the regression analysis suggest that insurers' size is, on average, associated with a positive and statistically significant impact on their solvency, suggesting larger insurers tend to show better solvency levels. The asset risk variable measuring the fraction of bond investments to total investments shows a positive effect on insurers' solvency, in line with the expectation that bonds are a relatively safe asset class. Leverage and non-insurance activities are negatively impacting insurers' solvency in both Z-score estimations on a statistically significant level, underlining the importance of maintaining a conservative capital structure as well as a focus on insurance activities to improve solvency levels. Increasing levels of underwriting risk are negatively associated with insurers' solvency, in line with the expectation that higher underwriting losses put pressure on solvency levels. The use of reinsurance surprisingly does not show a statistically significant effect but can be explained as the robustness checks regarding the sample split between P/C and L&H insurers show opposite effects for P/C and L&H. Age, as an approximation for the insurers' experience, shows a significant positive relationship, and while being in a group, on average, tends to increase the insurers' solvency, being a stock insurer tends, on average, to decrease it.

Table 6: Regression Results with Sector Indication

	Dependent Variable	
	Z-score (1)	Z-score (TS) (2)
HHI	0.446***	0.278***
	p = 0.000	p = 0.001
Size	0.055***	0.040***
	p = 0.000	p = 0.000
Asset Risk	0.301***	0.144**
	p = 0.000	p = 0.042
Leverage	- 0.168***	- 0.149***
	p = 0.000	p = 0.000
Non-Insurance Activities	- 0.039***	- 0.043***
	p = 0.000	p = 0.000
Underwriting Risk	- 0.154***	- 0.115***
	p = 0.000	p = 0.000
Reinsurance	- 0.001	0.070
	p = 0.984	p = 0.158
Age	0.113***	0.131***
	p = 0.000	p = 0.000
Group	0.087**	0.046
	p = 0.026	p = 0.218
Ownership	- 0.064	- 0.113***
	p = 0.115	p = 0.003
Concentration: Financials	0.043	0.080*
	p = 0.399	p = 0.086

Concentration: Public Admin.	0.104*	0.144***
	p = 0.059	p = 0.005
Concentration: Industrials	- 0.135	- 0.138
	p = 0.683	p = 0.681
Concentration: Real Estate	- 0.355***	- 0.278***
	p = 0.001	p = 0.001
Concentration: Energy	0.229	0.513*
	p = 0.421	p = 0.068
Concentration: Consumer Staples	0.247	0.190*
	p = 0.110	p = 0.084
Year Fixed Effects	Y	Y
Firm Clustered SE	Y	Y
Observations	21,038	20,949
R2	0.116	0.178
Adj. R2	0.115	0.177

Note: *p<0.1; **p<0.05; ***p<0.01
Table 6 shows the results of the OLS panel regression on the model given by Equation (2) from 2009 to 2018. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year, and the dependent variables, the size variable and the age variable are in logarithmic terms. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. All panel regressions are estimated with year-fixed effects and clustered standard errors at the insurer level. Model (1) refers to the Z-score estimated by means of a three-year rolling window over the RoA observations, and Model (2) refers to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

We also test the effect of sectoral asset concentrations on insurers' solvency by means of their reported RBC ratios. In contrast to the Z-score, the levels of the RBC ratios are affected by the prescribed capital requirements underlying the respective RBC formulas. Table 7 shows the results of the analysis, underlining the findings of the main analysis. Sectoral asset concentrations are generally positively associated with insurers' solvency in terms of the RBC ratio. While concentrations toward the financial and public sector are, on average, positive for the solvency situation, concentrations toward the industrial and real estate sector, on average, have a negative solvency impact. .

Table 7: Regression Results: RBC Ratio

	Dependent Variable	
	RBC Ratio (1)	RBC Ratio (2)
HHI	0.549***	0.535***
	p = 0.000	p = 0.000
Size	- 0.075***	- 0.076***
	p = 0.000	p = 0.000
Asset Risk	0.956***	0.910***
	p = 0.000	p = 0.000
Leverage	- 0.219***	- 0.219***
	p = 0.000	p = 0.000

Non-Insurance Activities	- 0.004**	- 0.003
	p = 0.034	p = 0.137
Underwriting Risk	0.163***	0.165***
	p = 0.000	p = 0.000
Reinsurance	- 0.344***	- 0.344***
	p = 0.000	p = 0.000
Age	0.121***	0.121***
	p = 0.000	p = 0.000
Group	0.267***	0.270***
	p = 0.000	p = 0.000
Ownership	- 0.062***	- 0.059***
	p = 0.000	p = 0.000
Concentration: Financials		0.036*
		p = 0.076
Concentration: Public Admin.		0.064***
		p = 0.006
Concentration: Industrials		- 0.245***
		p = 0.003
Concentration: Real Estate		- 0.089*
		p = 0.053
Concentration: Energy		0.104
		p = 0.496
Concentration: Consumer Staples		- 0.006
		p = 0.943
Year Fixed Effects	Y	Y
Firm Clustered SE	Y	Y
Observations	20,194	20,194
R2	0.212	0.212
Adj. R2	0.211	0.211

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7 shows the results of the OLS panel regression using the reported RBC ratio at an authorized control level as a dependent variable. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year, and the dependent variables, the size variable and the age variable are in logarithmic terms. All panel regressions are estimated with year-fixed effects and clustered standard errors at the insurer-level. *Own Table*.

3.6 Robustness Checks

We also test further model specifications. Firstly, we test the potential for the sectoral asset concentration to show a non-linear impact on insurers' solvency, i.e., concentrations up to certain threshold levels are associated with different effects. We include a squared term of the sectoral HHI variable in the regression model and standardize the coefficients to reduce the potential for structural multicollinearity. Table 13 (Appendix A.5) underlines the generally positive impact of sectoral asset concentrations on insurers' solvency and shows a disproportionate effect, i.e., there is an increasingly positive impact on the solvency for higher concentration levels. This appears plausible since higher levels of the sectoral HHI are associated with higher investment allocations toward the public sector. Consistent with the baseline findings, asset concentrations toward the real estate sector show a negative impact on insurers' solvency.

Secondly, we test for differences in the effect of the sectoral asset concentrations on insurers' solvency per asset type. To maintain the interdependency of the invested asset types in relation to the insurers' solvency, we include indicator variables on whether the asset concentration is related to the investments in bonds, stocks, direct real estate, mortgage loans, and long-term assets. Table 14 (Appendix A.5) underlines the findings of the baseline model regarding the effects of sectoral asset concentrations and shows that investments in stocks and real estate influence insurers' solvency negatively. Long-term assets, which cover particularly private equity and hedge fund investments, also show a negative association with insurers' solvency, whereas investments concentrated in bonds are associated with a positive impact on solvency.

Thirdly, to study if sectoral asset concentrations show a different impact between P/C insurers and L&H insurers, we split the sample accordingly. The findings in Tables 15 (P/C) and 16 (L&H) in Appendix A.5 underline the findings of the main model, i.e., sectoral asset concentrations in general are positively associated with insurers' solvency and that asset concentrations toward the real estate sector reduce the solvency levels, on average. Interestingly, while underwriting risk is negatively associated with the insurers' solvency in both sub-samples, the use of reinsurance is positively associated only with the sub-sample of P/C insurers and negatively associated with the sub-sample of L&H insurers. The existence of negative effects related to the use of reinsurance appears plausible. As Lei (2019) shows, the effect of reinsurance on insurers' financial performance can be considered as a cost-benefit trade-off. The cost of reinsurance can be overall detrimental to the solvency of L&H insurers, as the benefits of L&H reinsurance for smoothing underwriting risk are relatively small. In P/C insurance, the cost of reinsurance is likely to be outweighed by the benefits of risk mitigation. The opposite effects of the use of reinsurance on insurers' solvency in the two samples explains the correspondingly inconclusive effect found in the main model.

Furthermore, Tables 17, 18, and 19 estimate the main regression model, including firm-fixed effects (Appendix A.5). The within-firm variation of the sectoral asset concentrations of insurers over time is relatively limited and could be absorbed by including firm-fixed effects (see Table 1). In that regard, we expect the Z-score estimated by means of a three-year rolling window over the RoA observations, compared to the full time series, to provide more variation in the data for an estimation. Table 17, based on the more volatile Z-score measure using the three-year rolling window estimation, shows results similar to the main findings. The significance of the findings on the sectoral HHI measure drops when using the less volatile Z-score estimated by means of the full time series of RoA observations (Table 18) but increases again when removing the logarithmic scale of the Z-score that reduced its variation (Table 19). Considering these three regression specifications together, we interpret the results as overall robust to the introduction of firm fixed effects.

Moreover, we assess the potential bias in the results due to multicollinearity by determining the correlation of the explanatory variables. Table 20 (Appendix A.5) shows only weak levels of correlation across the variables, suggesting no material multicollinearity-related bias in the results

3.7 Policy Implications

Our findings suggest a link between sectoral asset concentrations and insurers' solvency. Sectoral asset concentrations can be beneficial for their solvency, in line with recent findings on the banking side by Beck et al. (2022), but it depends on the sectors in which asset portfolios are concentrated. While asset concentrations in the public sector improve insurers' solvency, in line with a low systematic risk typically associated with corresponding sovereign debt instruments, asset concentrations toward the real estate sector weaken it. This is not surprising given the sector's inherent risk of speculative bubbles (Fabozzi et al., 2020) and its role in triggering the 2007 to 2009 global financial crisis, which caused substantial losses to financial institutions (McDonald and Paulson, 2015).

From a prudential perspective on insurers' solvency, the findings suggest that the explicit exclusion of sectoral asset concentrations from the capital requirements of major regulatory frameworks, such as the U.S. RBC framework and Solvency II for the EU, can lead to inaccurate assessments of the systematic loss potential for insurers. The solvency capital currently set aside by insurers may not be appropriately allocated to the portfolio's concentration risk exposure, particularly in terms of the elevated loss potential associated with a sectoral concentration in the real estate sector. In that regard, emphasizing the loss potential of sectoral asset concentrations in insurance regulation can set incentives for insurers to mitigate risk exposures and strengthen their resilience against financial shocks.

In banking regulation, some jurisdictions, such as the United Kingdom (UK), apply a sectoral HHI for determining capital surcharges regarding sectoral concentration risks (BoE, 2021). However, based on our findings, a "one-size-fits-all" approach in terms of applying a single concentration risk measure aggregated over all sectoral investments of the insurer does not seem to be appropriate since the results show differences in the sector-specific effects of asset concentrations on insurers' solvency.

To improve the regulatory treatment of sectoral asset concentrations and to set appropriate regulatory incentives for insurers to diversify their assets from a sectoral perspective, a first step could be to introduce explicit public disclosure requirements on insurers' sectoral asset concentrations, for instance, as part of the regulatorily prescribed own risk assessments to evaluate the adequateness of their capital endowments (Own Risk and Solvency Assessment—ORSA). More transparency about the investment behavior of insurers as regards the sectoral asset allocations can result in market discipline effects by investors against those insurers that concentrate their assets too strongly.

Moreover, it could be beneficial to define regulatory benchmark levels of sectoral asset concentrations for monitoring purposes. Any deviation from these benchmark levels in the insurers' asset portfolio could then be considered as an increase in the sectoral concentration risk exposure that should be monitored and mitigated. These sectoral benchmark levels could be defined by sector-specific threshold levels in relation to the portfolio's total asset value. The quantitative determination of sectoral benchmark levels is, however, a difficult task. One approach could be to employ a capital allocation scheme (e.g. Dhaene et al., 2012; Urban et al., 2004; Merton and Perold, 1993), in which a portfolio's risk measure, for instance, the Value-at-Risk (VaR) is compared between asset portfolios with varying sectoral asset concentrations and a benchmark portfolio. The benchmark portfolio represents a well-diversified asset portfolio regarding sectoral asset concentrations, with the objective to ensure a specific VaR of the portfolio's asset returns. Comparing the VaR of the insurers' real-world asset portfolio with the VaR of the benchmark portfolio can be the basis for supplementary sectoral capital charges.[13] In particular, given the results of our regression analysis, a regulatory benchmark for asset concentrations in the real estate sector should be established

4. Conclusion

This study sheds light on the link between sectoral asset concentrations and insurers' solvency and develops implications for insurance regulation. By analyzing the dynamics of sectoral asset concentrations and their impact on insurers' financial health, we offer a complementary perspective on the complexities of the investment behavior of insurers and the corresponding regulatory treatment, compared to previous studies.

By creating a detailed dataset of U.S. insurers' asset holdings from 2009 to 2018 by means of their statutory filings, we identify material asset concentrations toward sectors such as finance, real estate, and the public sector, and we find that sectoral asset concentrations can be both beneficial and detrimental to the insurers' solvency, conditional on the specific sector in which the asset portfolio is concentrated. In particular, while asset concentrations toward the public sector significantly improve insurers' solvency, asset concentrations toward the real estate sector significantly weaken it.

Our findings can serve as a starting point for revising current regulatory practices since frameworks, such as the U.S. RBC, neglect sector concentration risk of assets in the determination of capital requirements. In that regard, the current capital requirements could lead to inaccurate estimates of the systematic loss exposure of concentrated asset portfolios, particularly in the real estate sector, and lack incentives for corresponding risk mitigation.

We, therefore, propose that insurance regulation be revised accordingly, in particular with a view to developing proactive measures to incentivize insurers to mitigate the accumulation of systematic risks associated with sectoral asset concentrations. A first step could be to increase the public disclosure requirements for insurers regarding their sectoral asset concentrations to foster market discipline, for instance as part of their own risk and solvency assessments (ORSA). In addition, sectoral benchmarks could be established through capital allocation schemes to indicate whether insurers are exposed to material concentration risks and may require closer supervision.

While we focus our analysis on the U.S. RBC, we expect our recommendations to apply to other frameworks as well, such as Solvency II for the EU, which also neglects sectoral asset concentrations in determining capital requirements. Moreover, as sectoral asset concentrations are increasingly discussed from a macroprudential perspective,

13. Banking regulation shows examples in this regard, in which the sectoral concentration in credit portfolios can be explicitly charged with supplementary capital (e.g., ESRB, 2020; Bank of England, 2017). An explicit reflection of sectoral asset concentration risk in insurance regulation would lead to a conceptually similar treatment for banks and insurers and can thus mitigate regulatory arbitrage.

our findings help to synchronize microprudential and macroprudential objectives in this regard.

In order to assess sector concentration risk more comprehensively, future research could explore sector-specific information asymmetries with respect to insurers as investors, as well as different risk management objectives regarding strategic asset allocation. It is also important to further study the potential macroprudential aspects of sectoral asset concentrations, as the corresponding investment behavior of insurers as large-scale investors can materially affect systemic risk, for instance, through fire sales (e.g. Ellul et al., 2011). In that regard, further research is needed to align microprudential and macroprudential objectives to avoid unintended consequences. Asset allocations found optimal for the individual institution, reflecting particular hedging goals or sector expertise (Che et al., 2021), may not be optimal from a systemic perspective due to common asset exposures across the institutions (e.g., Wagner, 2010)

.

Appendix A

A.1 Asset Concentration Risk Under Solvency II

As to Solvency II, we focus our discussion on its Standard Formula, as it is implemented by most insurers in the European Union (EU) (European Insurance and Occupational Pensions Authority [EIOPA], 2018c; Commission Delegated Regulation [EU] 2015/35). Asset concentration risk is covered in an explicit sub-module within the market risk module, and the corresponding capital charges aim to mitigate idiosyncratic risk exposures stemming from name concentration risk (EIOPA, 2014). A concentration risk capital charge is required if an insurer's aggregated investment in a single name exceeds a predetermined threshold in a range of 1.5% to 15% of the insurer's total assets, depending on the credit rating of the asset. The capital requirements by this sub-module are applicable to several financial instruments, comprising bonds, loans other than residential mortgage loans, equity, and property investments. Government bonds issued by member states of the European Economic Area (EEA) in their domestic currency are exempted from concentration risk charges (Commission Delegated Regulation [EU] 2015/35; EIOPA, 2014).[14]

Technically, the solvency capital requirement for name concentration risk is intended to cover the loss in the insurer's equity capital that would result from an instantaneous drop in the aggregated value of all assets in the portfolio referring to the same name (counterparty). The solvency capital charge for a specific name is determined as

$$SCR^{SF}_{conc,x} = s_{sf} \max[A_{conc,x} - T_x A, 0]$$

where $SCR^{SF}_{conc,x}$ denotes the Standard Formula's solvency capital requirement w.r.t.; the concentration risk of name x; s_{sf} the applicable shock factor depending on the credit quality step (CQS) of the asset with respect to name x; $A_{conc,x}$ the aggregated value of all assets related to name x; T_x the relative excess exposure threshold depending on the credit quality step of name x; and A the portfolio's total asset value (Commission Delegated Regulation [EU], 2015/35). The solvency capital requirement for the portfolio's total asset concentration risk over all names is given by the square root of the sum of squared single name SCRs, i.e., $SCR^{SF}_{Conc} = \sqrt{\sum_{x=1}^{X} (SCR_{conc,x})^2}$.

The credit quality steps under Solvency II range from 0 to 6 and reflect external ratings on the loss potential of the asset (Commission Delegated Regulation [EU], 2015/35). The excess exposure thresholds and the corresponding applicable shock factors in relation to the weighted average credit quality step of the single name exposure are given in Table 8.

Table 8: Shock Scenarios in Solvency II's Standard Formula

CQS	0	1	2	3	4	5	6
Threshold T_x	3%	3%	3%	1.5%	1.5%	1.5%	1.5%
Risk factor s_{sf}	12%	12%	21%	27%	73%	73%	73%

Own Table, based on Commission Delegated Regulation (EU) 2015/35.

14. A threshold of 15% is applied for covered bonds with the best credit rating. Immovable property has a threshold of 10% and a risk charge of 12%. Assets without a credit assignment, such as equity instruments, are considered to have a credit quality step (CQS) of 5 (Commission Delegated Regulation [EU], 2015/35).

The aggregation of capital requirements over all different names leads to the asset portfolio's total capital requirement in the asset concentration risk sub-module. However, the aggregation assumes no correlation between these different names in the portfolio and neglects the assets' sector-specific linkages due to common risk exposures, i.e., the assets' systematic risk exposures, which can lead to biased solvency capital requirements.

Like the U.S. risk-based capital (RBC) framework, Solvency II reflects only name concentration risk in the solvency capital requirements for asset concentration risk. However, the corresponding capital requirements differ substantially in their calculation, although both frameworks consider name concentration risk similarly as the risk of an accumulation of idiosyncratic risk exposures compared to a well-diversified asset portfolio. While Solvency II focuses on the asset portfolio's idiosyncratic risk exposure to each name (counterparty) in the portfolio, the U.S. RBC framework considers only the 10 largest names in the portfolio.

A.2 Sectoral Asset Concentrations of EU Insurers in 2018

Table 9 highlights the sectoral asset allocations to the five most important sectors for EU insurers in 2018.

Table 9: Overview of the Five Most Important Sectors for EU Insurers in 2018

NACE Sector	Min (%)	Max (%)	Mean (%)
K - Financial and Insurance Activities	17.6% (Croatia)	70.6% (Germany)	42.4%
K64 - Financial Services	8.6% (Croatia)	56.6% (Iceland)	30.4%
O - Public Sector	2.4% (Iceland)	67.2% (Hungary)	35.2%
C - Manufacturing	0.3% (Hungary)	11.2% (Finland)	3.9%
L - Real Estate	0.2% (Poland)	12.0% (Norway)	2.9%
D - Electricity and Gas	0.1% (Hungary)	5.8% (Iceland)	1.9%

Table 9 shows the minimum, maximum, and mean ratio at the country-level of insurers' sectoral asset allocations in 2018. Data is based on Nomenclature of Economic Activities (NACE) classification and provided by European Insurance and Occupational Pensions Authority (EIOPA) (2019a). K64 is a subsector of the financial sector K and mainly comprises banking-like activities.

A.3 Data for the Sectoral Asset Concentrations in U.S. Insurers' Asset Portfolios

We collect insurers' statutory filings with the NAIC from 2009 to 2018 from S&P Global Market Intelligence. Our analysis is based on raw data as reported by life, health, and property/casualty (P/C) insurers to the NAIC with regard to investment schedules A (part 1: direct property), B (part 1: mortgage loans on real estate), D (part 1: bonds; part 2, section 1: preferred stocks; part 2, section 2: common stocks) and BA (part 1: other long-term invested assets, especially private equity funds, hedge funds). The data does not contain assets held by insurers on separate accounts.

The raw dataset provides the assets' Committee on Uniform Security Identification Procedures (CUSIP) numbers and book/adjusted carrying values (BACV). We match the assets' CUSIP numbers with sector classification variables stemming from several other data sources: Bloomberg, Refinitiv Eikon, Center for Research in Security

Prices (CRSP), and Municipal Securities Rulemaking Board (MSRB). For the sector classifications, we use the Global Industry Classification Standard (GICS) as the main sectoral classification system. If a GICS classification is not available for a given asset, we aim to get the Thomson Reuters Economic Sector variable. Public Administration is originally not included in the GICS system, but we add it as an additional sector to comprise the typically large public debt investments of insurers.

For assets we cannot match with a sector classification variable, we use the line numbers that are reported with the assets and match them with the GICS classification system if possible. We classify schedule A and B investments as real estate sector investments in line with McDonald and Paulson (2015) to get an economic perspective on the insurers' risk exposures. For fund investments, we employ a "look-through" approach and classify these investments to a specific sector only if we are able to get information on the funds' actual investments. If we have no clear information for a fund investment, we denote it as unclassified in the sample. We exclude investments with a negative BACV. We also exclude investments that are described as housing tax credits since it is unclear which sectoral risk exposure is most appropriate to describe the value of this asset type, for example, the public, the real estate, or the financial sector.

Table 10 gives an overview of the insurance sector's BACV in our sample. For example, in 2018, our sample comprises assets with a value of U.S. $5,800 billion. For 88% of the total assets, we have a sector classification in 2018, hence, 12% of the total assets cannot be allocated to a specific business sector. Table 11 is extending Table 1 by showing the time series of the sectoral asset allocations in the entire sample.

Table 10: Data Coverage of the U.S. Insurance Sector's Assets in our Sample

Year	Total BACV (bn U.S.-$)	Sectoral Coverage
2018	5803	0.88
2017	5133	0.86
2016	4980	0.84
2015	4779	0.84
2014	4738	0.84
2013	4600	0.83
2012	4410	0.82
2011	4332	0.81
2010	4169	0.80
2009	3949	0.80

Table 10 shows the data coverage in our sample of the U.S. insurance sector's total assets as book/adjusted carrying value (BACV) per year. The column "Sectoral Coverage" shows the extent of the total assets for which we have a sectoral classification. Investment data stems from S&P Global Market Intelligence. *Own Table*.

Table 11: Year-by-Year Sectoral Asset Concentrations of the U.S. Insurance Sample

Sector	2018	2017	2016	2015	2014	2013	2012	2011	2010	2009
Financials	0.33	0.35	0.33	0.33	0.32	0.31	0.31	0.30	0.30	0.29
Real Estate	0.13	0.05	0.05	0.05	0.06	0.06	0.06	0.07	0.09	0.10
Public Administration	0.10	0.12	0.12	0.12	0.13	0.13	0.14	0.15	0.15	0.16
Industrials	0.06	0.07	0.07	0.07	0.06	0.06	0.06	0.05	0.04	0.04

Utilities	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Health Care	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.02
Consumer Staples	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Energy	0.03	0.04	0.04	0.05	0.05	0.05	0.04	0.04	0.04	0.03
Information Technology	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.01
Consumer Discretionary	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.01
Materials	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.02
Communication Services	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01
Residual Sectors (each)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Unclassified Assets	0.12	0.14	0.16	0.16	0.16	0.17	0.18	0.19	0.20	0.20

Table 11, as extension to Table 1, shows the sectoral asset concentrations of the entire sample of 2,708 U.S. insurers from 2009 to 2018, as determined by the book/adjusted carrying value (BACV) of all sector-specific assets aggregated by all insurers in the sample divided by the aggregated BACV of all reported assets. Investment data comprises schedules A, B, D, and BA from the insurers' statutory filings with the NAIC. We follow McDonald and Paulson (2015) and include investments from Schedule A (direct property) and Schedule B (mortgage loans on real estate) under the real estate sector. *Own Table.*

A.4 Regression Variables

Table 12: Definition of Regression Variables

Variable	Description
Dependent Variables	
Z-score	Natural logarithm of the Z-score. Z-score as a measure of the insurers' solvency is the ratio of insurers' (RoA) (net income before taxes [EBT] divided by total net assets) plus capital-to-asset ratio (CaR) (ratio of total equity as insurance surplus to total net assets) divided by the standard deviation of the RoA using a three-year rolling window.
Z-score (TS)	Natural logarithm of the Z-score. In this specification, the standard deviation of the RoA is determined by means of the entire time series of observations.
RBC Ratio	Reported risk-based capital (RBC) ratio at authorized control level.
Explanatory Variables	
HHI	Herfindahl-Hirschman Index based on sectoral asset allocations. It is the sum of the squared ratios of the aggregated asset values (BACV) allocated to a specific sector to the portfolio's total value of assets.
Size	Natural logarithm of total net assets.[15] Larger institutions tend to be more financially stable due to their larger asset and underwriting risk pools benefiting more from risk diversification effects. For instance, Shim (2017b) and Liebenberg and Sommer (2008) find a positive impact of the insurers' size on its financial performance. However, large insurers might also be incentivized to engage in excessive risk-taking as they might be considered "too-big-to-fail," which could reduce the insurers' solvency (Financial Stability Oversight Council [FSOC], 2013).

15 Reported variable by insurers as the sum of all assets in all lines reported, excludes any valuation allowance, i.e., excludes assets for which the state does not allow the company to take credit.

Asset Risk	Ratio of bond-related investments to total assets. Insurers tend to be conservative investors regarding the seniority of the assets they invest in. Typically, large fractions of the insurers' asset portfolio consist of fixed-income bond investments (Section 3.2). Compared with stock investments, bonds are typically less risky as they provide the investor with a higher claim on the issuing firm's assets in case of a bankruptcy. Therefore, we measure the portfolio's asset risk as the ratio of bond-related investments to total assets. In this regard, a higher ratio of bonds in the asset portfolio of an insurer indicates a safer asset portfolio in terms of a lower exposure against financial shocks, potentially harming the insurers' solvency. In this regard, Shim (2017b) finds a positive influence of the ratio of bond investments to total investments on the insurers' solvency.
Leverage	Ratio of total net premiums earned to policyholder surplus. Insurers typically finance their assets by policyholder premiums, i.e., their underwriting business and not by issuing debt obligations. Therefore, in contrast to banks, which finance uncertain asset returns mainly by certain debt obligations under potentially material duration mismatches, the insurers' leverage needs to be determined differently as for banks. We follow Shim (2017b) and estimate the insurers' leverage as the ratio of total net premiums earned to policyholder surplus. The surplus is an equity position determined by the difference between assets and liabilities, reflecting the financial resilience of an insurer to a shock. A higher leverage due to a lower underwriting-related policyholder surplus can harm the insurers' solvency, for instance in case of an underwriting shock leading to material increases in insurance reserves. Shim (2017b), Chen and Wong (2004), and Carson and Hoyt (1995) show that higher leverage ratios can reduce the solvency of insurers.
Non-Insurance Activities	Ratio of total liabilities to policy holder surplus. Insurers also engage in non-insurance related activities like securities lending or derivatives trading that can affect the insurers' solvency (e.g., International Association of Insurance Supervisors [IAIS], 2019). For instance, losses from securities lending activities have been a major source for AIG's near-collapse during the global financial crisis from 2007 to 2009 (McDonald and Paulson, 2015). Therefore, we follow Bierth et al. (2015) and Weiß and Mühlnickel (2014) and control for non-insurance-related activities by means of determining the ratio of total liabilities to policyholder surplus.
Concentration: Sector	Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector.
Underwriting Risk	Based on Che et al. (2021), we measure underwriting risk by the rolling standard deviation of the underwriting loss ratio (losses incurred and loss adjustment expenses to premiums earned) over the previous three years, and winsorize it at the 99th percentile to reduce the impact of outliers. Higher underwriting risk, particularly in terms of unexpected losses not properly reflected in the pricing of insurance premiums, can be negatively associated with the financial performance of insurers.
Reinsurance	Following Che et al. (2021), the variable is defined as the reinsurance ratio, which is determined as the ratio of premiums ceded to premiums written. Reinsurance is a typical risk mitigation tool of insurers, particularly to protect the ceding company against unexpected underwriting losses. A higher reinsurance ratio could therefore be beneficial to the financial performance of an insurer.

Age	Natural logarithm of age. In relation to Che et al. (2021), the variable is determined as the difference between the year of the observation and the entity's year established. A higher age of the insurer could be associated with higher levels of investment experience as regards specific sectors, i.e., sector-specific information advantages that might lead to abnormal investment returns.
Group	Indicator variable, equal to 1 if the entity is part of a group, and 0 otherwise, to account for systematic differences in the corporate structure of the insurers (e.g., Che et al., 2021; Leverty and Grace, 2018; Shim, 2017a; 2017b).
Ownership	Indicator variable, equal to 1 if the entity is a stock insurer, and 0 if it is a mutual insurer, to account for systematic differences in the ownership structure of the insurers (e.g., Che et al., 2021; Leverty and Grace, 2018; Shim, 2017a; 2017b).

Table 12 describes the variables used in the regression analysis. *Own Table*.

A.5 Robustness Checks

Table 13: Regression Results: Non-Linearity

	Dependent Variable			
	Z-score	Z-score (TS)	Z-score	Z-score (TS)
	(1)	(2)	(3)	(4)
HHI^2	0.041**	0.036**	0.043***	0.038**
	p = 0.011	p = 0.017	p = 0.007	p = 0.011
HHI	0.073***	0.037*	0.061**	0.027
	p = 0.003	p = 0.100	p = 0.012	p = 0.233
Size	0.132***	0.097***	0.126***	0.093***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Asset Risk	0.084***	0.053***	0.066***	0.032**
	p = 0.000	p = 0.000	p = 0.000	p = 0.039
Leverage	- 0.400***	- 0.354***	- 0.396***	- 0.351***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Non-Insurance Activities	- 0.161***	- 0.176***	- 0.150***	- 0.165***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Underwriting Risk	- 0.099***	- 0.074***	- 0.097***	- 0.073***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Reinsurance	0.002	0.022	0.001	0.022
	p = 0.918	p = 0.134	p = 0.943	p = 0.135
Age	0.108***	0.127***	0.107***	0.126***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Group	0.082**	0.041	0.084**	0.044
	p = 0.036	p = 0.278	p = 0.032	p = 0.246
Ownership	- 0.068*	- 0.119***	- 0.063	- 0.112***
	p = 0.095	p = 0.002	p = 0.122	p = 0.004
Concentration: Financials			0.043	0.080*
			p = 0.391	p = 0.085
Concentration: Public Admin.			0.108**	0.147***
			p = 0.048	p = 0.004

Concentration: Industrials			- 0.144	- 0.147
			p = 0.662	p = 0.661
Concentration: Real Estate			- 0.354***	- 0.277***
			p = 0.001	p = 0.001
Concentration: Energy			0.217	0.502*
			p = 0.450	p = 0.077
Concentration: Consumer Staples			0.269*	0.209*
			p = 0.087	p = 0.059
Year Fixed Effects	Y	Y	Y	Y
Firm Clustered SE	Y	Y	Y	Y
Observations	21,038	20,949	21,038	20,949
R2	0.114	0.175	0.117	0.180
Adj. R2	0.114	0.174	0.116	0.179

Note: *p<0.1; **p<0.05; ***p<0.01
Table 13 shows the results of the OLS panel regressions (Tables 5 and 6) including a squared term of the sectoral HHI measure to test for non-linearity. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one-year, the dependent variables are in logarithmic terms. Except for the indicator variables, the control variables are scaled to reduce the potential for structural multicollinearity. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. All panel regressions are estimated with year-fixed effects and clustered standard errors at the insurer level. Models (1) and (3) refer to the Z-score estimated by means of a three-year rolling window over the RoA observations, and Models (2) and(4) refer to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

Table 14: Regression Results: Asset Type

	Dependent Variable			
	Z-score	Z-score (TS)	Z-score	Z-score (TS)
	(1)	(2)	(3)	(4)
HHI	0.508***	0.323***	0.462***	0.276***
	p = 0.000	p = 0.000	p = 0.000	p = 0.001
Size	0.051***	0.037***	0.052***	0.037***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Leverage	- 0.169***	- 0.150***	- 0.169***	- 0.150***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Non-Insurance Activities	- 0.038***	- 0.043***	- 0.037***	- 0.042***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Underwriting Risk	- 0.152***	- 0.116***	- 0.150***	- 0.115***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Reinsurance	0.010	0.073	0.007	0.072
	p = 0.850	p = 0.137	p = 0.886	p = 0.142
Age	0.110***	0.132***	0.110***	0.132***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Group	0.107**	0.060	0.105***	0.058
	p = 0.007	p = 0.111	p = 0.007	p = 0.121
Ownership	- 0.043	- 0.102***	- 0.042	- 0.100***
	p = 0.296	p = 0.008	p = 0.307	p = 0.009

Concentration: Financials			0.131***	0.136***
			p = 0.005	p = 0.002
Concentration: Public Admin.			0.207***	0.209***
			p = 0.000	p = 0.000
Concentration: Industrials			- 0.109	- 0.135
			p = 0.727	p = 0.673
Concentration: Energy			0.614*	0.874***
			p = 0.083	p = 0.008
Concentration: Consumer Staples			0.195	0.147
			p = 0.188	p = 0.185
Direct Real Estate	- 0.686***	- 0.743***	- 0.525**	- 0.577***
	p = 0.002	p = 0.000	p = 0.018	p = 0.000
Mortgages Loans	- 0.492*	- 0.447*	- 0.355	- 0.305
	p = 0.095	p = 0.061	p = 0.239	p = 0.205
Stocks	- 0.149***	- 0.082*	- 0.075	- 0.007
	p = 0.002	p = 0.063	p = 0.122	p = 0.882
Long-Term Assets	- 1.187***	- 0.537***	- 1.015***	- 0.362***
	p = 0.000	p = 0.000	p = 0.000	p = 0.004
Year Fixed Effects	Y	Y	Y	Y
Firm Clustered SE	Y	Y	Y	Y
Observations	21,238	21,149	21,238	21,149
R2	0.111	0.172	0.114	0.178
Adj. R2	0.110	0.171	0.113	0.177

Note: *p<0.1; **p<0.05; ***p<0.01
Table 14 shows the results of the OLS panel regressions (Tables 5 and 6) including indicator variables for the asset type in which the insurer concentrated its assets (Bonds, Stocks, Direct real estate, Mortgage loans, and Long-term assets). Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one-year, the dependent variables, the size variable, and the age variable are in logarithmic terms. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. To reduce multicollinearity, the variable "asset risk" has been excluded, as it measures the fraction of bond investments to total investments, which is highly correlated with the indicator variable for the asset type of bonds. The same rationale holds for the concentration indicator on real estate and the asset type indicators for real estate. All panel regressions are estimated with year-fixed effects and clustered standard errors at the insurer-level. Models (1) and (3) refer to the Z-score estimated by means of a three-year rolling window over the RoA observations, and Models (2) and (4) refer to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

Table 15: Regression Results: P&C Sub-Sample

	Dependent Variable			
	Z-score	Z-score (TS)	Z-score	Z-score (TS)
	(1)	(2)	(3)	(4)
HHI	0.529***	0.324***	0.497***	0.277***
	p = 0.000	p = 0.002	p = 0.000	p = 0.006
Size	0.065***	0.048***	0.064***	0.046***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Asset Risk	0.372***	0.248***	0.261***	0.143*
	p = 0.000	p = 0.000	p = 0.002	p = 0.062

Leverage	- 0.198***	- 0.155***	- 0.196***	- 0.153***
	p = 0.000	p = 0.002	p = 0.000	p = 0.002
Non-Insurance Activities	- 0.149***	- 0.161***	- 0.146***	- 0.158***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Underwriting Risk	- 0.208***	- 0.148***	- 0.205***	- 0.144***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Reinsurance	0.163***	0.188***	0.174***	0.197***
	p = 0.010	p = 0.002	p = 0.006	p = 0.002
Age	0.081***	0.108***	0.078***	0.105***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Group	0.105**	0.074*	0.105**	0.073*
	p = 0.016	p = 0.072	p = 0.016	p = 0.074
Ownership	- 0.096**	- 0.115***	- 0.093**	- 0.114***
	p = 0.034	p = 0.006	p = 0.037	p = 0.006
Concentration: Financials			0.099*	0.065
			p = 0.067	p = 0.213
Concentration: Public Admin.			0.176***	0.161***
			p = 0.003	p = 0.005
Concentration: Industrials			- 0.062	- 0.170
			p = 0.854	p = 0.620
Concentration: Real Estate			- 0.275**	- 0.291***
			p = 0.029	p = 0.005
Concentration: Energy			0.201	0.388*
			p = 0.512	p = 0.051
Concentration: Consumer Staples			0.209	0.102
			p = 0.164	p = 0.339
Year Fixed Effects	Y	Y	Y	Y
Firm Clustered SE	Y	Y	Y	Y
Observations	16,236	16,167	16,236	16,167
R2	0.138	0.200	0.140	0.206
Adj. R2	0.137	0.199	0.139	0.205

Note: *p<0.1; **p<0.05; ***p<0.01
Table 15 shows the results of the OLS panel regressions for the sub-sample of P/C insurers. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year, and the dependent variables, the size variable, and the age variable are in logarithmic terms. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. All panel regressions are estimated with year-fixed effects and clustered standard errors at the insurer level. Models (1) and (3) refer to the Z-score estimated by means of a three-year rolling window over the RoA observations, and Models (2) and (4) refer to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

Table 16: Regression Results: L&H Sub-Sample

	Dependent Variable			
	Z-score	Z-score (TS)	Z-score	Z-score (TS)
	(1)	(2)	(3)	(4)
HHI	0.451**	0.359*	0.397**	0.400**
	p = 0.012	p = 0.066	p = 0.025	p = 0.046
Size	0.077***	0.057***	0.074***	0.053***
	p = 0.000	p = 0.001	p = 0.000	p = 0.003
Asset Risk	0.534***	0.399**	0.444***	0.294*
	p = 0.000	p = 0.013	p = 0.009	p = 0.098
Leverage	- 0.112***	- 0.110***	- 0.110***	- 0.107***
	p = 0.000	p = 0.002	p = 0.000	p = 0.002
Non-Insurance Activities	- 0.044***	- 0.040***	- 0.042***	- 0.039***
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Underwriting Risk	- 0.071*	- 0.077*	- 0.071*	- 0.076*
	p = 0.067	p = 0.063	p = 0.064	p = 0.072
Reinsurance	- 0.447**	- 0.307*	- 0.438**	- 0.288*
	p = 0.011	p = 0.073	p = 0.013	p = 0.092
Age	0.101**	0.118**	0.100**	0.122**
	p = 0.027	p = 0.024	p = 0.028	p = 0.019
Group	- 0.157	- 0.176*	- 0.151	- 0.166
	p = 0.112	p = 0.086	p = 0.125	p = 0.102
Ownership	- 0.098	- 0.228*	- 0.095	- 0.225*
	p = 0.460	p = 0.089	p = 0.476	p = 0.092
Concentration: Financials			- 0.028	0.137
			p = 0.781	p = 0.127
Concentration: Public Admin.			0.025	0.041
			p = 0.844	p = 0.747
Concentration: Industrials			- 0.311	0.135
			p = 0.380	p = 0.414
Concentration: Real Estate			- 0.427***	- 0.220*
			p = 0.007	p = 0.087
Concentration: Energy			0.200	0.835
			p = 0.752	p = 0.351
Year Fixed Effects	Y	Y	Y	Y
Firm Clustered SE	Y	Y	Y	Y
Observations	4,802	4,782	4,802	4,782
R2	0.132	0.169	0.136	0.176
Adj. R2	0.128	0.166	0.131	0.172

Note: *p<0.1; **p<0.05; ***p<0.01

Table 16 shows the results of the OLS panel regressions for the sub-sample of L&H insurers. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year, and the dependent variables, the size variable, and the age variable are in logarithmic terms. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. No undertaking had a maximum asset concentration toward the consumer staples sector. All panel regressions are estimated with year-fixed effects and clustered standard errors at the insurer level. Models (1) and (3) refer to the Z-score estimated by means of a three-year rolling window over the RoA observations, and Models (2) and (4) refer to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

Table 17: Regression Results: Firm Fixed Effects: Z-score Specification 1

	Dependent Variable	
	Z-score	Z-score
	(1)	(2)
HHI	0.162**	0.156**
	p = 0.025	p = 0.033
Size	0.136***	0.136***
	p = 0.000	p = 0.000
Asset Risk	0.214**	0.194**
	p = 0.010	p = 0.025
Leverage	- 0.154***	- 0.153***
	p = 0.000	p = 0.000
Non-Insurance Activities	- 0.050***	- 0.049***
	p = 0.000	p = 0.000
Underwriting Risk	- 0.094***	- 0.094***
	p = 0.000	p = 0.000
Reinsurance	0.009	0.007
	p = 0.890	p = 0.915
Age	- 0.131**	- 0.134**
	p = 0.013	p = 0.011
Group	0.065	0.019
	p = 0.861	p = 0.960
Ownership	- 0.003	- 0.005
	p = 0.952	p = 0.926
Concentration: Financials		- 0.036
		p = 0.307
Concentration: Public Admin.		- 0.027
		p = 0.494
Concentration: Industrials		- 0.358**
		p = 0.030
Concentration: Real Estate		- 0.263***
		p = 0.001
Concentration: Energy		- 0.186
		p = 0.278
Concentration: Consumer Staples		0.128
		p = 0.526
Year Fixed Effects	Y	Y
Firm Fixed Effects	Y	y
Firm Clustered SE	Y	Y
Observations	21,038	21,038
R2	0.546	0.546
Adj. R2	0.479	0.480

Note: $*p<0.1$; $**p<0.05$; $***p<0.01$

Table 17 shows the results of the OLS panel regressions of the baseline model, including firm fixed effects in addition to the year-fixed effects and the clustered standard errors at the insurer level. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year, and the dependent variables, the size variable, and the age variable are in logarithmic terms. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. Models (1) and (2) refer to the Z-score estimated by means of a three-year rolling window over the RoA observations. *Own Table*.

Table 18: Regression Results: Firm Fixed Effects: Z-score Specification 2

	Dependent Variable	
	Z-score (TS)	Z-score (TS)
	(1)	(2)
HHI	0.013	0.016
	p = 0.590	p = 0.508
Size	- 0.092***	- 0.093***
	p = 0.000	p = 0.000
Asset Risk	- 0.014	- 0.002
	p = 0.647	p = 0.935
Leverage	- 0.071***	- 0.071***
	p = 0.000	p = 0.000
Non-Insurance Activities	- 0.059***	- 0.059***
	p = 0.000	p = 0.000
Underwriting Risk	0.002	0.002
	p = 0.692	p = 0.697
Reinsurance	- 0.115***	- 0.115***
	p = 0.000	p = 0.000
Age	- 0.022	- 0.021
	p = 0.203	p = 0.224
Group	1.531***	1.522***
	p = 0.000	p = 0.000
Ownership	0.013	0.013
	p = 0.477	p = 0.481
Concentration: Financials		- 0.025**
		p = 0.022
Concentration: Public Admin.		- 0.035***
		p = 0.003
Concentration: Industrials		- 0.026
		p = 0.523
Concentration: Real Estate		- 0.098***
		p = 0.003
Concentration: Energy		- 0.104*
		p = 0.065
Concentration: Consumer Staples		- 0.087**
		p = 0.012
Year Fixed Effects	Y	Y
Firm Fixed Effects	Y	y
Firm Clustered SE	Y	Y

Observations	20,949	20,949
R2	0.939	0.939
Adj. R2	0.930	0.930

Note: *p<0.1; **p<0.05; ***p<0.01
Table 18 shows the results of the OLS panel regressions of the baseline model, including firm fixed effects in addition to the year-fixed effects and the clustered standard errors at the insurer level. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year, and the dependent variables, the size variable, and the age variable are in logarithmic terms. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. Models (1) and (2) refer to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

Table 19: Regression Results: Firm Fixed Effects: Z-score Specification 2: Non-Logarithmic

	Dependent Variable	
	Z-score (TS)	Z-score (TS)
	(1)	(2)
HHI	1.916***	1.933***
	p = 0.000	p = 0.000
Size	1.37e-08*	1.42e-08*
	p = 0.081	p = 0.072
Asset Risk	- 0.177	- 0.132
	p = 0.679	p = 0.760
Leverage	- 0.551***	- 0.550***
	p = 0.000	p = 0.000
Non-Insurance Activities	- 0.821***	- 0.819***
	p = 0.000	p = 0.000
Underwriting Risk	0.168**	0.167**
	p = 0.024	p = 0.024
Reinsurance	- 0.739*	- 0.734*
	p = 0.061	p = 0.063
Age	0.707	0.714
	p = 0.531	p = 0.530
Group	27.664***	27.637***
	p = 0.003	p = 0.003
Ownership	0.299	0.299
	p = 0.302	p = 0.302
Concentration: Financials		- 0.104
		p = 0.488
Concentration: Public Admin.		- 0.145
		p = 0.397
Concentration: Industrials		- 0.248
		p = 0.622
Concentration: Real Estate		- 0.488*
		p = 0.097
Concentration: Energy		- 0.715
		p = 0.533

Concentration: Consumer Staples		- 0.639
		p = 0.296
Year Fixed Effects	Y	Y
Firm Fixed Effects	Y	y
Firm Clustered SE	Y	Y
Observations	20,949	20,949
R2	0.966	0.966
Adj. R2	0.961	0.961

Note: *p<0.1; **p<0.05; ***p<0.01
Table 19 shows the results of Table 18 but without a logarithmic specification. Definitions of the variables are provided in Appendix A.4. Explanatory variables are lagged by one year. Variables with the prefix "Concentration" are indicators equal to 1 if an insurer has the maximum of its assets (percentage of sector-specific assets to total assets) in the given year concentrated in the respective sector. Models (1) and (2) refer to the Z-score estimated by means of the insurers' entire time series of RoA observations. *Own Table*.

Table 20: Correlation Matrix of the Explanatory Variables

	HHI	Asset Risk	Size	Leverage	Non-Insurance Activities	Underwriting Risk	Reinsurance	Age
HHI	1							
Asset Risk	0.11	1						
Size	-0.35	-0.03	1					
Leverage	-0.07	0.12	0.13	1				
Non-Insurance Activities	-0.22	0.15	0.45	0.37	1			
Underwriting Risk	0.05	0.02	-0.06	-0.10	-0.01	1		
Reinsurance	0.15	0.08	0.05	-0.19	-0.16	-0.08	1	
Age	-0.17	-0.21	0.23	0.02	0.12	-0.05	-0.05	1

Table 20 shows the correlation coefficients of the continuous explanatory variables. *Own Table*.

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