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Insurance Business Diversification and Systemic Risk*

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Abstract

The global financial crisis of 2007-09 has shown that an individual institution's distress can cause systemic risk by means of financial contagion. Since business diversification can typically lower the distress risk of an individual institution, it should also lower potential contagion risks resulting from an economic shock to the institution and thus, reduce the institution's contribution to systemic risk. This paper studies if insurance business diversification between life and non-life insurance can reduce systemic risk stemming from an individual insurer's distress. The paper provides empirical evidence that diversified multiline insurers that engage in both insurance lines have, on average, a lower contribution to systemic risk than monoline insurers. More specifically, insurers with a business allocation in the range of 54% life insurance show, on average, the lowest contribution to systemic risk in terms of financial contagion. These findings have important implications for the design of macroprudential regulatory frameworks in the insurance sector, as the role of business diversification between life and non-life insurance for systemic risk has not been taken into account so far.

Keywords: Financial Institutions, Systemic Risk, Diversification

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1 Introduction

The near-collapse of AIG during the global financial crisis of 2007–09 is a prominent example how insurers can contribute to systemic risk from the ”domino” perspective. In that regard, systemic risk is considered as the adverse consequences of an individual institution’s distress for the real economy, in particular due to financial contagion from the distressed institution to other institutions in the economy (e.g. European Insurance and Occupational Pensions Authority (EIOPA) (2019), International Association of Insurance Supervisors (IAIS) (2019b), International Monetary Fund (IMF) (2016)). Therefore, macroprudential regulation developed in the aftermath of the crisis the concept of systemically important insurers, which aims to lower contagion risks by means of reducing the distress risk of insurers, in particular on the basis of increased monitoring by supervisors and higher capital requirements (European Insurance and Occupational Pensions Authority (EIOPA) (2019), International Association of Insurance Supervisors (IAIS) (2016a)).

Since business diversification can typically lower the distress risk of a financial institution (e.g. Köhler (2015), Stiroh (2006)), business diversification might also lower systemic risk from the ”domino” perspective. If a financial institution gets hit by a shock, potential coinsurance effects between business lines could reduce the institution’s distress risk and thus, lower the potential for financial contagion resulting in systemic risk. For insurers, life and non-life insurance typically show different underwriting characteristics that might generate a coinsurance effect that could lower systemic risk. However, the insurance literature provides no clear evidence on the influence of business diversification between life and non-life insurance on insurer’s distress risk, making it unclear if insurers can actually lower systemic risk by means of business diversification. Therefore, I analyze in this paper if a diversification potential between life and non-life insurance exists and to what extent it potentially affects the insurer’s contribution to systemic risk in terms of financial contagion.

Clarifying the role of insurer’s business diversification for financial stability is important for macroprudential insurance regulation, since it has not been taken into account so far. For instance, the IAIS aims to conduct an ”individual insurer monitoring” by means of an indicator-based assessment methodology, which particularly focuses on the insurer's size and its financial obligations, but does not consider a potential influence of insurance business diversification on systemic risk (International Association of Insurance Supervisors (IAIS) (2019b), International Association of Insurance Supervisors (IAIS) (2018)).[1] If insurers can influence contagion risks stemming from their distress by means of business diversification, macroprudential regulation should take this into account in order to derive a more precise assessment of the systemic importance of insurers.

Therefore, I study in Section 2.1 the differences in the underwriting characteristics between life and non-life insurance and potential implications on the insurer's distress risk. Quantitative evidence on the cash flow distribution of both insurance lines suggests that cash flows from life insurance business are less volatile, and mainly uncorrelated with cash flows from the more volatile non-life insurance business, which offers the potential for coinsurance effects between both insurance lines. This rationale is underlined by the distribution of the Z-Score as a frequently used measure for an institution's distress risk, which shows significantly higher stability levels for diversified insurers engaging in both insurance lines compared to undiversified monoline insurers.

Motivated by the individually stabilizing diversification effect, I analyze in Section 2.2 based on an exemplary portfolio model how business diversification between life and non-life insurance can influence systemic risk stemming from financial contagion. I focus on counterparty risk as an exemplary channel for financial contagion, which can cause an initial shock to an individual insurer to propagate through an economic system and cause additional losses to the insurer's counterparties. More specifically, I study the impact of diversification across both insurance lines on the expected loss of a counterparty that holds a financial claim to the insurer, e.g. resulting from subordinated debt issues or securities lending activities.[2] Due to the imperfectly correlated cash flows from life and non-life insurance, I find a u-shaped relation between counterparty risk and the business allocation between both insurance lines, which ultimately yields a risk minimizing

[1] The "individual insurer monitoring" of the IAIS aims to assess systemic risk stemming from contagion risks as a result of an individual insurer's distress. For that, the IAIS adopted in 2019 an updated indicator-based methodology, which will first be applied in 2020 within the new holistic systemic risk framework (International Association of Insurance Supervisors (IAIS) (2019b)). Until 2020, the old indicator-based methodology from 2016 is applied (International Association of Insurance Supervisors (IAIS) (2019a), International Association of Insurance Supervisors (IAIS) (2016a)).

[2] Counterparty risk is an important source for systemic risk (e.g. International Association of Insurance Supervisors (IAIS) (2019b)). For example, during the global financial crisis 2007-09, AIG lost approximately 21 bn US$ as a counterparty in security lending activities, which contributed substantially to AIG's role for systemic risk (McDonald and Paulson (2015)).

business allocation with an overweight towards the less volatile life insurance business.

I test in Section 3 the theoretically predicted u-shaped relation between business diversification and financial contagion empirically. I employ the $\Delta CoVaR$ as frequently used measure for systemic risk stemming from financial contagion on a large and global sample of 102 insurance companies from 2004-2017. The regression results suggest a significant u-shaped relation between business diversification in terms of life and non-life insurance and systemic risk. Monoline insurers conducting only life or non-life insurance show, on average, the highest levels of systemic risk in terms of financial contagion. In particular, systemic risk can be minimized by an average business allocation in the range of 54% life insurance, hence 46% non-life insurance.

Due to the link between business diversification and systemic risk, I discuss in Section 4 potential policy implications of the findings. Since macroprudential insurance regulation does not take the extent of business diversification between life and non-life insurance into account, the findings suggest that supervisors could use the level of the insurer's business allocation as a further indicator for assessing the systemic relevance of insurance companies. An allocation-dependent assessment could increase the precision in determining which insurers are systemically important, and hence, which insurers should be monitored more closely. Based on the derived findings, monoline life and monoline non-life insurers should be monitored more closely than diversified insurers, as these undiversified insurers are associated with higher contagion risks if they get hit by a shock.

This paper is based on a broad stream of literature. By providing evidence on a general diversification potential between life and non-life insurance for the stability of an individual insurer, it adds further insights to the insurance diversification literature. While work by, for instance, Shim (2017b), Che and Liebenberg (2017), Berry-Stölzle et al. (2012), Elango et al. (2008), Liebenberg and Sommer (2008) focus on diversification-related performance effects within the non-life insurance business, evidence regarding a diversification potential between life and non-life insurance is scarce. In that regard, findings by the European Insurance and Occupational Pensions Authority (EIOPA) (2018) show that insurers engaging in both insurance lines experienced less distress events in the past, suggesting the existence of a coinsurance effect between life and non-life insurance. Therefore, my findings underline that insurance business diversification can be beneficial for lowering an insurer's individual distress risk, and by that, as well for lowering systemic risk from financial contagion.

The findings of this paper also contribute to the systemic risk literature, in particular, with a focus on the determinants of an insurer's contribution to systemic risk caused by its distress. Previous work, for instance Kaserer and Klein (2019), Irresberger et al. (2017), Bierth et al. (2015), Weiß and Mühlnickel (2014), Cummins and Weiss (2014) and Billio et al. (2012), study the influence of multiple insurer-related characteristics and activities on systemic risk in the insurance sector. However, most of these studies categorize insurers either into life or non-life insurers and hence, neglect potential diversification effects between both insurance lines with regard to systemic risk. Kaserer and Klein (2019) include the categorization of multiline insurers into their analysis, but do not distinguish between different business allocation levels for multiline insurers. In contrast, I employ a continuous measure of the insurer's business allocation and thus, study the marginal influence of business diversification on systemic risk.

Moreover, the findings contribute to the synchronization of micro- and macroprudential regulation. While microprudential insurance regulation focuses on reducing the individual insurer's distress risk, it does not consider potential implications of its measures on a macroeconomic level (European Insurance and Occupational Pensions Authority (EIOPA) (2017)). Microprudential frameworks like Solvency II or the Global Insurance Capital Standard (ICS) consider a diversification effect between life and non-life insurance business for the calculation of solvency capital requirements by means of a zero correlation between both insurance lines.[3] However, such a diversification effect remains unconsidered in macroprudential regulation, for instance, in terms of the designation of systemically important insurers by the IAIS (e.g. International Association of Insurance Supervisors (IAIS) (2019b)). Hence, providing evidence how business diversification affects both, individual distress risk and contagion risk helps to further synchronize micro- and macroprudential regulation.

The rest of the paper is structured as follows. Section 2 studies the diversification potential between life and non-life insurance and its influence on the insurer's contribution to systemic risk by means of financial contagion. Section 3 analyzes the influence of business diversification on insurer's contribution to systemic risk empirically by conducting a regression analysis. Section 4 discusses potential policy implications and Section 5 concludes.

[3]Directive 2009/138/EC, Annex IV, Point (1) for Solvency II and International Association of Insurance Supervisors (IAIS) (2020) for the ICS).

2 The Link between Business Diversification, Individual Distress Risk and Systemic Risk

The case of AIG during the global financial crisis from 2007-09 has shown that the distress of an individual insurer can cause systemic risk, as the huge losses that AIG has incurred, mainly resulting from its CDS and security lending transactions (McDonald and Paulson (2015)), caused substantial contagion risks to other institutions in the financial system. More specifically, these contagion risks were related to three main sources that caused the systemic relevance of AIG (Financial Stability Oversight Council (FSOC) (2013b)): i) the counterparty risks of other financial institutions to AIG, ii) potential loss spirals in asset prices from a liquidation (fire-sale) of AIG's assets that could cause substantial losses to other institutions and iii) a lack of substitutability for policyholders in the commercial insurance market, in which AIG was a market player. After the financial crisis, macroprudential insurance regulation developed the concept of systemically important insurers in order to limit systemic risk stemming from contagion risks due to an individual insurer's distress. The main objective in that regard is to lower an insurer's distress risk and thereby lowering contagion risks, in particular with regard to the three main sources that resulted in AIG's systemic importance (e.g. European Insurance and Occupational Pensions Authority (EIOPA) (2019), International Association of Insurance Supervisors (IAIS) (2019b)).

Eling and Jia (2018) show that the insurer's distress risk is related to the volatility of its business activities. Thus, the diversification of insurance lines should, from a portfolio perspective, reduce the volatility of a diversified insurer's equity cash flow and hence, reduce its distress risk, which should reduce financial contagion and systemic risk. Interestingly, business diversification has not been taken into account so far by macroprudential regulation when assessing systemic risk in the insurance sector (International Association of Insurance Supervisors (IAIS) (2019a), International Association of Insurance Supervisors (IAIS) (2016a)). Thus, the question arises: Can insurers actually generate such a stabilizing diversification potential with an impact on systemic risk?

Life and non-life insurance might yield a diversification benefit for financial stability, as they typically show substantially different underwriting characteristics. However, evidence on the diversification potential between life and non-life insurance is scarce, since most studies focus only on the non-life insurance sector (e.g. Shim (2017b), Che and Liebenberg (2017), Berry-Stölzle et al.

(2012), Elango et al. (2008), Liebenberg and Sommer (2008)). Therefore, I study in the subsequent section whether life and non-life insurance can potentially yield a stabilizing diversification benefit for insurers.

2.1 Cash Flow Characteristics of Insurance Activities

Life insurance is typically considered as a relatively long-term business, and the underlying insurance claims and the growth in insurance reserves are usually more predictable than that in the short-term non-life insurance business (Gründl et al. (2016), Insurance Europe (2014)). For example, death benefit payments in life insurance are fixed upon the purchase of contracts, whereas indemnity payments in non-life insurance substantially vary due to an ex ante uncertain loss severity. Hence, non-life insurers can be subject to substantial payout tails that are difficult to predict (Cummins and Weiss (2016)). However, both insurance lines offer products that can be strongly exposed to macroeconomic shocks, for instance trade credit insurance (non-life) or annuity products with guaranteed returns (life insurance), which lowers the diversification potential of such products with regard to financial stability compared to pure indemnity products (International Association of Insurance Supervisors (IAIS) (2016b)).

Additionally, insurers conduct an "inverted production cycle", meaning that insurance premiums are paid by policyholders up-front and independent from any potentially emerging insurance claims, leading to a very stable premium income during the duration of an insurance contract (Bank of England (BoE) (2015a)). In that regard, the typical duration of a life insurance contract is more than 10 years, whereas it is typically one year for non-life insurance contracts (Bank of England (BoE) (2015b), European Insurance and Occupational Pensions Authority (EIOPA) (2014a)). Hence, non-life insurers can adjust premiums frequently, for instance due to market competition or changes in the loss distribution of underwriting risks, which makes the premium income from non-life insurance products usually more prone to fluctuations over time compared to life insurance products.

These typical characteristics suggest that cash flows from non-life insurance tend to be more volatile than cash flows from life insurance (Bank of England (BoE) (2015b). For insurers providing both insurance lines, a diversification potential yielding coinsurance effects could exist.[4] As

[4]For example, by means of profit and loss transfer agreements, a holding company consisting of a life and a

insurers tend to have a high asset commonality despite different business models, for instance due to regulatory incentives in terms of risk and rating based capital requirements, it is likely that a potentially stabilizing diversification effect between life and non-life insurance mainly stems from coinsurance effects between both underwriting portfolios (e.g. Getmansky et al. (2018), Bank of England (BoE) (2014), Financial Stability Oversight Council (FSOC) (2013a)).

Table 1 underlines the different underwriting characteristics between life and non-life insurance by providing empirical evidence on the cash flow growth rates regarding the insurers' premium income and underwriting payments. The growth rates of both cash flow streams subsume the typical insurance related characteristics and should provide information about a potential diversification effect between both insurance lines.

Life insurers have, on average, substantially lower volatility levels in their premium and claim cash flows (0.12/0.27) compared to non-life insurers (0.23/0.58). Since the average correlation between life and non-life insurers with regard to both cash flows is close to zero (0.02/0.03), a diversification benefit between both insurance lines is likely to exist. Hence, a coinsurance effect between both insurance lines should arise that lowers the insurer's distress risk.

	Life	Non-Life	Correlation
Premium Income	0.12	0.23	0.02
Underwriting Claims and Benefits	0.27	0.58	0.03

Table 1: Volatility and Correlation of Premium and Claim Cash Flows

This Table shows the average volatility (standard deviation) of the annual growth rates with regard to insurers' cash flows from premium income and cash flows from underwriting claims and benefits. Correlation shows the average Pearson correlation coefficient across the insurers' growth rates. Premium income is measured by the growth rates on insurers' net premiums earned in the life insurance line, approximated by Life&Health insurance, and in the Non-Life insurance line, approximated by P&C insurance. Underwriting claims and benefits is measured by insurers' growth rates on claims and benefit payments in the respective insurance lines. The sample consists of 56 insurers from 2005-2019 and data is retrieved from SNL Financial (Market Intelligence) in US$. Details on the sample and data is given in Appendix A.1.

In order to study if a diversification benefit materializes for financial stability, I study the distribution of the Z-Score as frequently used measure of an institution's level of individual stability (e.g. Shim (2017a), Köhler (2015), Laeven and Levine (2009), Stiroh and Rumble (2006)). Details on the sample and data used for calculating insurers' Z-Scores is provided in Appendix A.2. The Z-Score is defined as

non-life insurance subsidiary can hedge losses from one insurance line with outcomes from the other insurance line.

$$Z - Score_{i,t} = \frac{RoA_{i,t} + CAR_{i,t}}{Std(RoA)_{i,t}} \tag{1}$$

where $Z - Score_{i,t}$ means the Z-Score of institution i in year t, $RoA_{i,t}$ denotes the return on assets of institution i in year t, which is calculated as net income before taxes (EBT) divided by total assets, $CAR_{i,t}$ denotes the capital-to-asset ratio of institution i in year t, which is calculated as the ratio of total equity to total assets. $Std(RoA)_{i,t}$ corresponds to the standard deviation of the return on assets based on a three-year rolling window.

Table 2 shows the distribution of Z-Scores between undiversified (monoline) insurers that engage only in life or non-life insurance and diversified insurers engaging in both insurance lines (multiline). A higher Z-score corresponds to lower individual distress risk, thus, a higher level of individual stability.

Multiline insurers show across every quantile substantially larger Z-Scores, ranging from 0.23 to 1970, compared to monoline insurers that show a range of 0.11 to 1430. Multiline insurers also have a significantly higher mean level of individual stability with a Z-Score of 57.1 compared to 42.6 for monoline insurers. Hence, the findings suggest lower distress risk due to diversification benefits between life and non-life insurance, which is supported by statistics on historic insurer distress events. The European Insurance and Occupational Pensions Authority (EIOPA) (2018) reports cases in the EU insurance sector from 1999-2016, showing that multiline insurers engaging in both lines had the fewest cases of insurer distress (32 cases), whereas non-life insurers had the most distress events with 95 cases, followed by life insurers with 51 cases. Moreover, Eling and Jia (2018) report similar failure rates for life and non-life insurers, but substantially lower failure rates for multiline insurers.

Variable	Min.	25%	Med	75%	Max.	t-test on means
Z-Score mono	0.11	11.00	21.84	45.84	1430.13	42.64
Z-Score multi	0.23	14.86	27.59	60.09	1970.04	57.07***

Table 2: Z-Score and t-test for Multiline and Monoline Insurers

This table shows the minimum, 25% quantile, median, 75% quantile and maximum of the Z-Scores between undiversified (monoline) and diversified (multiline) insurers from 2003-2018. The t-test is an unpaired t-test assuming unequal variances across both groups. The difference in the means between undiversified and diversified insurers (42.64/57.07) is significant at the 1% level. The list of insurers is given in Appendix A.2.

Thus, the quantitative evidence suggests a diversification effect of insurer's business diversification on distress risk. However, as the Z-Score is a measure of an individual institution's distress risk, it is not fully informative about how business diversification might influence financial contagion from a distressed institution to other institutions, and hence, how business diversification affects systemic risk. More specifically, solvency measures like the Z-Score or the Value at Risk (VaR) applied to a single institution from a microeconomic perspective do not capture how business diversification influences the tail dependence between the solvency conditions of institutions in a given economic system, and hence, how a shock can propagate losses through the system by means of financial contagion. Therefore, the subsequent part derives an economic intuition on the potential influence of business diversification on financial contagion from a macroeconomic perspective based on an exemplary portfolio model, and derives testable implications for empirical validation.

2.2 Business Diversification and Financial Contagion from a Portfolio Perspective

The model is intended to illustrate how business diversification might influence financial contagion from a distressed insurer to other institutions and hence, how it affects the insurer's contribution to systemic risk. It approximates systemic risk by means of counterparty (credit) risk, which is an important channel for shocks to cause systemic risk (International Association of Insurance Supervisors (IAIS) (2019b)). The model's underlying rationale is that if an insurer has financial linkages to other institutions, for example due to derivatives trading or security lending activities, and becomes distressed in case of a shock, it could propagate losses to its counterparties if it fails to repay its financial obligations.[5] In that regard, the model illustrates the case of AIG during the financial crisis 2007-09, as substantial losses from AIG's CDS and security lending transactions threatened the stability of the entire financial system due to contagion risks (McDonald and Paulson (2015)). Hence, business diversification in terms of life and non-life insurance should affect contagion risks as it lowers the insurer's distress risk.

The model is based on a portfolio perspective on an insurance holding that has the opportunity to invest in one life and one non-life insurance company. This set-up is analogous to the one

[5] In the first quarter of 2017, the sum of security repurchase agreements, loans and security lending liabilities comprised 2.3% (0.7%) of U.S. life (non-life) total liabilities (Board of the Governors of the Federal Reserve System (2017)).

employed by Kahane and Nye (1975) to examine the efficiency of insurance underwriting portfolios and more recently, Stiroh (2006) uses a similar framework to study diversification effects between interest and non-interest cash flows for banks. At time $t = 0$, the insurance holding invests the fraction $\alpha \in [0, 1]$ in the life (L) and the residual amount in the non-life (NL) insurance company. Both subsidiaries generate after one period of time normally distributed equity cash flows, R_L and R_{NL}, that are aggregated by the allocation term α to the holding company's total equity cash flow R.[6]

The insurance holding is obligated to serve a claim D to a counterparty at time $t = 1$. For instance, D might be the repayment of subordinated debt issued by the holding company at time $t = 0$. If the holding company is subject to financial distress, for example resulting from a shock to the subsidiaries' equity cash flows, the counterparty might suffer a loss due to financial contagion. The counterparty's expected loss can be described by using a truncated normal distribution as

$$EL = D - E[\min(D, R)] = (D - \mu_R)\,\Phi(\frac{D - \mu_R}{\sigma_R}) + \sigma_R\,\Phi'(\frac{D - \mu_R}{\sigma_R}) \qquad (2)$$

where Φ is the cumulative distribution function and Φ' the probability density function of the normal distribution, and μ_R and σ_R^2 are the expectation and variance of the insurance holding's equity cash flow R at time $t = 1$.

EL reflects the value of an European put option at strike D on the holding's equity cash flow R. If the holding's cash flow is smaller than D, the counterparty expects a loss in terms of $D - E[\min(D, R)]$. From option pricing theory it follows that the price of a European put option is increasing with the underlying asset's volatility.[7] Hence, the expected loss for the counterparty is influenced by the volatility of the holding's total equity cash flow, which is given by

$$\sigma_R^2 = \alpha^2\,\sigma_L^2 + (1 - \alpha)^2\,\sigma_{NL}^2 + 2\,\alpha\,(1 - \alpha)\,\sigma_L\,\sigma_{NL}\,\rho \qquad (3)$$

where ρ is the correlation between the life and non-life subsidiaries' equity cash flows, α denotes the fraction of the life insurance business with regard to the total equity cash flow R, σ_L and σ_{NL}

[6] It is assumed that the holding company has a profit and loss transfer agreement with its subsidiary companies and that the holding's investment decision does not affect the business activities of the operating companies, i.e. it does not affect the subsidiaries' existing capital structures.

[7] This follows from a positive vega of European put options.

denote the volatility of the equity cash flows from the life and non-life insurance subsidiaries.

The expected loss for the counterparty can then be reduced by finding a solution to the first order condition with regard to the business allocation parameter α. By assuming a negligible difference between the expected equity cash flows from life and non-life insurance for illustrative reasons, the first order condition is given by

$$\begin{aligned}\frac{\partial EL}{\partial \alpha} &= (D-\mu_R)\,\frac{\partial \Phi(z)}{\partial \alpha} + \frac{\partial \sigma_R}{\partial \alpha}\,\Phi'(z) + \sigma_R\,\frac{\partial \Phi'(z)}{\partial \alpha} \\ &= \frac{1}{2\sigma_R}\,\Phi'(z)\,\frac{\partial \sigma_R^2}{\partial \alpha}\end{aligned} \tag{4}$$

which yields the expected loss minimizing business allocation α^* for the holding company by the minimum variance portfolio allocation as

$$\alpha^* = \frac{\sigma_{NL}^2 - \sigma_L\,\sigma_{NL}\,\rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\,\sigma_L\,\sigma_{NL}\,\rho} \tag{5}$$

A detailed derivation is provided in Appendix A.3. Hence, business diversification between life and non-life insurance can reduce counterparty credit risk if the correlation ρ between the equity cash flows from both insurance lines is sufficiently small. Since Section 2 suggests almost uncorrelated cash flows from life and non-life insurance business, a multiline insurance company causes lower counterparty credit risk than either a life or non-life monoline insurer. Hence, the relationship between counterparty credit risk and the business allocation between life and non-life insurance can then be illustrated by a u-shaped relation. Since Section 2 suggests that life insurance is less volatile than non-life insurance, the fraction α^* that minimizes counterparty risk shows an overweight to life insurance business in order to reduce the volatility of the holding's total cash flow R.

3 Empirical Analysis

The theoretical intuition suggests for an empirical validation that business diversification between life and non-life insurance should have a u-shaped relation with systemic risk in terms of financial contagion, since business diversification has a theoretically u-shaped relation with counterparty (credit) risk. Hence, diversified multiline insurers should have a lower contribution to systemic risk than undiversified monoline insurers. More specifically, a systemic risk minimizing business allocation between life and non-life insurance should exist and be represented by an allocation with more than 50% life insurance business.

3.1 Regression Model

Dependent Variables

I employ the ΔCoVaR as an empirical systemic risk measure, which captures the potential that a distressed institution propagates additional losses to other institutions in a given system of institutions. The measure has been originally proposed by Adrian and Brunnermeier (2016), and has been used frequently under different estimation approaches in the literature (e.g. Brunnermeier et al. (2020), Bierth et al. (2015), Weiß and Mühlnickel (2014), Ergün and Girardi (2013), Mainik and Schaanning (2014)).[8] More specifically, the system's Value-at-Risk conditional on institution i being in distress, $\text{CoVaR}_{S|i}$, is defined as the q-quantile of the system's conditional return distribution

$$\mathbb{P}\left(r^S \leq \text{CoVaR}_{S|i}(q) \mid r^i \leq VaR^i(q)\right) = q, \tag{6}$$

where r^S and r^i denote the return of the system (S) and institution i.

Adrian and Brunnermeier (2016) suggest to measure an institution's systemic risk contribution, ΔCoVaR, by the difference between the system's tail risk upon an institution's shock, and the system's tail risk if the institution is in its median state. It is defined as

$$\Delta\text{CoVaR}_q^{S|i} = \text{CoVaR}_{r^i=VaR^i(q)}^{S|i} - \text{CoVaR}_{r^i=VaR^i(0.5)}^{S|i} \tag{7}$$

where q denotes the quantile level of equity returns for a given system S and insurer i. Since the tail dependence between an institution and the system might change over time or with the severity of shocks, e.g. fat tails, I follow Ergün and Girardi (2013) for the estimation of the ΔCoVaR

[8] The $CoVaR$ is directional in its measurement of financial contagion, i.e. an institution's high contribution to systemic risk does not imply a high exposure to systemic risk for that institution (e.g. Brunnermeier et al. (2020), Ergün and Girardi (2013)). For instance, a distressed systemically important insurer might cause a substantial loss to another institution (e.g. small and regional insurer), but does not have to be similarly exposed to a distress of the small insurer. Another example are lending activities: If institution A buys a bond of institution B, the distress of A does not have a contagion effect on B, but the distress of B has a contagion effect on A.

and include more severe distress events in the estimation by considering tail returns below the institution's VaR at a given quantile level. The measure is defined by

$$\Delta \text{CoVaR}_q^{S|i} = \text{CoVaR}^{S|i}_{r^i \leq VaR^i(q)} - \text{CoVaR}^{S|i}_{r^i \in [\mu^i \pm \sigma^i]} \tag{8}$$

where μ^i and σ^i are the mean and standard deviation of the insurer i's return, respectively.

The measure is estimated on a daily basis by fitting a DCC-GARCH model with normally distributed errors to the bivariate time series of the system's and insurer's stock returns based on 7-year rolling windows. In the analysis, I use the average daily value of the measure during the year under consideration for the insurer's systemic risk contribution in that year. In line with the literature, I employ the 5% quantile of stock returns as indicating financial distress (e.g. Bierth et al. (2015)).

For a further robustness of the results, I also measure the ΔCoVaR based on the historic quantiles of the joint return distribution between the system and the institution under consideration. For example, $CoVaR_{r^i \leq VaR^i(q)}$ is then the historical VaR of the system's return for a given quantile level q on days where a specific institution is in distress, i.e. the institution shows a return worse or at its VaR. The measure is estimated on 7-year rolling windows.

Since the ΔCoVaR is inversely related to an institution's contribution to systemic risk, I report negative values, such that a higher value relates to a higher systemic risk contribution. I exclude each insurer under consideration for estimating the system's returns, because otherwise, the results would be biased by a constructed correlation between the insurer and the system in case of a shock.

I employ two different systems for the risk measure. First, the financial system, consisting of roughly 37% banks, 26% real estate firms, 23% brokers and 14% insurers. Since the real estate sector has a strong link to the financial sector as shown in the global financial crisis 2007-09, it is included in the financial system for the analysis. Second, in contrast to previous studies that focus only on contagion risks from a distressed insurer to the financial system (e.g. Bierth et al. (2015), Weiß and Mühlnickel (2014)), I also employ a global non-financial (NoFIN) system in order to detect a more direct impact of the insurer's distress on the real economy. The non-financial sector is represented by Datastream's world non-financial index, which covers firms from different industrial sectors, e.g. food products, pharmaceuticals or software, and different geographical regions. A detailed description of both systems is given in Appendix A.4.

Independent Variables

The main variable of interest is the insurer's diversification extent between life and non-life insurance. Thus, I employ the ratio of net premiums earned in life and health insurance relative total net premiums earned (including life and non-life insurance).[9] The ratio is a continuous measure of the insurer's business diversification extent, as it indicates with a value of 0 a monoline non-life insurer and with a value of 1 a monoline life insurer. Hence, it is able to capture the marginal effect of changes in the business allocation on systemic risk, in contrast to dichotomous measures that categorize insurers only into diversified or undiversified insurers (e.g. Liebenberg and Sommer (2008)). Since I expect a u-shaped relation between business diversification and systemic risk, I employ a quadratic term in the regression model.

I control for several insurer characteristics. I approximate an insurer's size by the natural logarithm of its total assets, which, for instance, Weiß and Mühlnickel (2014) find to be significantly related to the insurer's systemic risk contribution. The rationale is that large firms are more likely to be too-big-to-fail as well as too-complex-to-fail than small firms, and hence, potentially engage in riskier activities and propagate shocks more easily to other institutions (International Association of Insurance Supervisors (IAIS) (2016a)). Moreover, large insurers are more likely to hold and sell similar assets, potentially causing adverse fire sale effects to other institutions, which increases systemic risk (e.g. Getmansky et al. (2018), Ellul et al. (2018), Ellul et al. (2011)). Hence, I expect size to increase an insurer's systemic risk contribution in terms of financial contagion.

I also control for the insurer's leverage and follow the rationale by Shim (2017a), Shim (2017b), Thimann (2014) and Kessler (2013) and refrain from employing a bank-oriented definition of the leverage measure, for instance, in terms of a debt or asset to equity ratio (e.g. Bierth et al. (2015), Weiß and Mühlnickel (2014)). Such a definition seems to be more appropriate for determining systemic risk in the banking sector, as these institutions typically finance their assets by means of

[9]Health business in that regard refers to premium income from health insurance products with similar underwriting characteristics than life insurance. These products are from a regulatory perspective typically allocated to life insurance (e.g. for Solvency II in the EU: Article 1 No. 38 and Annex I of COMMISSION DELEGATED REGULATION (EU) 2015/35, European Insurance and Occupational Pensions Authority (EIOPA) (2014b); for the US: e.g. 26 U.S. Code Section 816 (a/b)).

debt obligations under potentially substantial duration mismatches. The global financial crisis of 2007-09 has shown that severe duration mismatches between assets and liabilities can contribute to financial contagion with systemic consequences (Brunnermeier et al. (2009), Brunnermeier (2009)). However, since insurers typically finance their assets by premiums from policyholders and consider duration matching between assets and liabilities, economic shocks influence contagion risks from insurers differently compared to banks (Thimann (2014)). Hence, I define leverage as the ratio of net premiums earned to policyholder surplus defined as the difference between assets and liabilities (e.g. Shim (2017a)). Since Carson and Hoyt (1995) and Chen and Wong (2004) show that higher leverage ratios can increase the insurer's distress risk, I expect a higher leverage ratio to increase systemic risk.

Since insurers engage in non-insurance related activities that influence contagion risks, for instance derivatives trading or security lending activities as in the case of AIG (McDonald and Paulson (2015)), I control for non-core activities analogously to Bierth et al. (2015) by using the ratio of total liabilities over insurance reserves. I expect a higher ratio to increase the potential for financial contagion and hence, to increase systemic risk in case an insurer becomes distressed.

As insurers are conservative investors, a higher return on their investments could increase their profitability and resilience against shocks. Thus, a higher return on investments might lower the insurer's contribution to systemic risk. However, higher returns might also be associated with higher investment risk, which could increase the insurer's contribution to systemic risk. Interestingly, Weiß and Mühlnickel (2014) and Bierth et al. (2015) find no significant relation of the insurer's profitability measured by the return on assets on the insurer's systemic risk contribution. I employ the insurer's return on investments, defined as the ratio of investment income to total assets, but expect the influence on systemic risk to be unrestricted.

I conduct the multivariate panel regression on the following model

$$Y_{i,t} = \beta_0 + \beta_1 Life^2_{i,t-1} + \beta_2 Life_{i,t-1} + \beta_Z Z_{i,t-1} + \epsilon_{i,t} \quad (9)$$

where $Y_{i,t}$ stands for the ΔCoVaR systemic risk measure of institution i in year t, $Life_{i,t}$ denotes the ratio of life insurance business and $Z_{i,t}$ denotes the control variables. $\epsilon_{i,t}$ denotes the error term.

Table 14 in Appendix A.5 gives an overview of all variables used for the panel regression analysis. I account for aggregate macro-economic trends, for example, the transition to the low interest rate environment on capital markets, and regional trends, such as changing insurance demand or the regulatory environment, by including year and geographic fixed effects. I also cluster standard errors at the insurer level, in order to account for serial correlation within the insurer-data.

Since the business allocation of insurers is relatively persistent, for instance 52% of all insurers in the sample used for the regression are monoline insurers, I follow van Oordt and Zhou (2018) and Liebenberg and Sommer (2008) by refraining from using insurer-fixed effects, as it would otherwise absorb most of the variation in the data. In order to mitigate reverse causality inducing endogeneity in the regression model, for instance, in the sense that insurers adjust their business allocation to the contemporaneous level of systemic risk, I follow Bierth et al. (2015) and Weiß and Mühlnickel (2014) by lagging all explanatory variables by one year.

Due to the quadratic term for the life ratio, the model might suffer from structural multi-collinearity. Hence, I standardize the regression parameters with mean 0 and standard deviation 1, which also increases comparability between the marginal effects of the independent variables (e.g. López-Espinosa et al. (2009)).[10]

3.2 Data

The insurer sample consists of 102 insurers over the period 2004-2017.[11] Table 3 shows the descriptive statistics, and the list of insurers is given in Appendix A.5. The sample consists of 48% multiline insurers, followed by 31% non-life insurers and 21% life insurers. Most insurers are located in Europe (42%), followed by North America (34%), Asia-Pacific (13%), Middle East (7%) and Africa (4%). Hence, it covers a wide spectrum of institutional types and geographical areas.

The distribution of the $\Delta\text{CoVaR}_{hist}$ based on historic return quantiles is close to Weiß and Mühlnickel (2014), whereas the distribution of the ΔCoVaR_{EG} proposed by Ergün and Girardi (2013) is close to Bierth et al. (2015).[12] Interestingly, the average of the model-free $\Delta\text{CoVaR}_{hist}$ is larger than that of the ΔCoVaR_{EG}, suggesting the latter measure is less capable of capturing

[10] In the robustness checks, I also test the model with unscaled data, showing similar results.

[11] I exclude insurer-year observations with negative policyholder surplus (assets-liabilities) and negative life ratios.

[12] Bierth et al. (2015) and Weiß and Mühlnickel (2014) differ substantially in the estimation process and financial systems used for assessing the insurer's contribution to systemic risk.

extreme loss spillovers across institutions.[13]

An economic shock to the average insurer in the sample increases the global financial and non-financial system's tail risk due to financial contagion by roughly 3% based on $\Delta\text{CoVaR}_{hist}$, and by roughly 1% based on ΔCoVaR_{EG}. Hence, in line with the literature, distressed insurers can contribute to systemic risk by causing additional losses to other institutions.

The average insurer allocates a fraction of 42% of its insurance business to life insurance, which, interestingly, constitutes an overweight to non-life insurance. The average size of an insurer in the sample is 107 billion US$ in total assets, which is larger than in Bierth et al. (2015) and Weiß and Mühlnickel (2014). The sample also includes very small insurers, with about 64 million US$, and very large insurers with 1057 billion US$.

Statistic	Mean	St. Dev.	Min	Max
$\Delta\text{CoVaR}_{hist}$ (FIN)	0.036	0.014	−0.002	0.054
$\Delta\text{CoVaR}_{hist}$ (NoFIN)	0.031	0.013	−0.002	0.048
ΔCoVaR_{EG} (FIN)	0.009	0.005	−0.001	0.028
ΔCoVaR_{EG} (NoFIN)	0.007	0.004	−0.0002	0.019
Total Assets (bn US$)	107.36	192.88	0.064	1056.96
Total Liabilities (bn US$)	97.16	179.41	0.026	985.45
Life Ratio	0.422	0.390	0.000	1.000
Net Claims Ratio	0.896	0.569	0.033	8.39
Leverage	1.300	0.858	0.007	7.249
Non-Core Act.	7.703	53.812	1.011	891.999
Debt/Asset Ratio	0.075	0.099	0.000	0.626
Debt/Equity Ratio	0.760	1.627	0.000	14.134
RoI	0.031	0.028	−0.371	0.149

Table 3: Descriptive Statistics

The table shows the descriptive statistics for the global sample of 102 insurers over the time period 2004-2017 used in the regression analysis. The sample consists of 941 firm-year observations. $\Delta\text{CoVaR}_{hist}$ denotes the CoVaR measure based on historical quantiles, ΔCoVaR_{EG} denotes the CoVaR measure according to Ergün and Girardi (2013). Definitions and data sources are given in Appendix A.5. The table also contains several variables used for robustness checks. Total Assets and Total Liabilities are given in billion US Dollar.

3.3 Results

Table 4 presents the results of the panel regression, suggesting the existence of a u-shaped relation between business diversification and systemic risk, since the quadratic and linear terms of

[13] The difference between both measures might stem from the assumption of normally distributed error terms in ΔCoVaR_{EG} by Ergün and Girardi (2013).

the life ratio are significantly related to the systemic risk measures and have different signs. Thus, monoline insurers that engage only in life or non-life insurance contribute more to systemic risk by means of financial contagion than multiline insurers.

	Dependent variable:			
	ΔCoVaR$_{hist}$ (FIN)	ΔCoVaR$_{hist}$ (NoFIN)	ΔCoVaR$_{EG}$ (FIN)	ΔCoVaR$_{EG}$ (NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	0.440***	0.333*	0.442**	0.453**
	$p = 0.007$	$p = 0.067$	$p = 0.018$	$p = 0.014$
$Life$	−0.509***	−0.395**	−0.478**	−0.497**
	$p = 0.006$	$p = 0.049$	$p = 0.017$	$p = 0.012$
$Total\ Assets$	0.343***	0.350***	0.485***	0.510***
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$Leverage$	0.050	0.055	0.031	0.032
	$p = 0.153$	$p = 0.110$	$p = 0.298$	$p = 0.320$
$Non-Core\ Act.$	0.031**	0.021	0.0001	0.001
	$p = 0.011$	$p = 0.167$	$p = 0.993$	$p = 0.930$
RoI	0.006	0.002	0.009	0.010
	$p = 0.766$	$p = 0.910$	$p = 0.686$	$p = 0.638$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	941	941	941	941
R^2	0.836	0.803	0.821	0.807
Adjusted R^2	0.832	0.798	0.817	0.802
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: OLS Panel Regression

The table shows the results of the OLS panel regression on the model given by Equation 9 from 2004 to 2017. Variable definitions and data sources are provided in Appendix A.5. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ refers to the CoVaR measure on historical quantiles w.r.t. the global financial (FIN) and non-financial (NoFIN) system. ΔCoVaR$_{EG}$ refers to the same systems, but uses the estimation technique by Ergün and Girardi (2013). Regression parameters are standardized with mean 0 and standard deviation 1.

In particular, monoline non-life insurers ($Life = 0$) reduce, on average, their contribution to systemic risk in the financial sector as measured by the ΔCoVaR$_{hist}$ by 0.509 standard deviations for an increase in the life ratio by 1 standard deviation.[14] Monoline life insurers ($Life = 1$) reduce, on average, their contribution to systemic risk in the financial sector measured by ΔCoVaR$_{hist}$ by 0.028 standard deviations for a decrease in the life ratio by 1 standard deviation.[15] Hence, systemic

[14] Due to scaling of the regression parameters, their marginal effects on the dependent variable are expressed in terms of standard deviations. The marginal effect of the life ratio on the insurer's systemic risk contribution can be generally expressed as: $\Delta Y = (2\hat{\beta}_1 Life + \hat{\beta}_2)\Delta Life$, with ΔY in standard deviations of Y and $\Delta Life$ in standard deviations of the life ratio. Hence, for $Life = 0$: $\Delta Y = \hat{\beta}_2$. The marginal effect of the life ratio can also be expressed in unit changes by exchanging $\Delta Life$ with $= 0.0256$, since a 1% change in the life ratio corresponds to 0.0256 std_{Life}.

[15] A 1 std decrease in life ratio results in a change of the allocation from $L = 1$ to $L = 0.61$, which corresponds to $\Delta Y = -(2\hat{\beta}_1 0.61 + \hat{\beta}_2)\Delta Life$, yielding a change of the insurer's systemic risk contribution by -0.028 std of the

risk from insurer's distress and financial contagion is reduced more strongly if non-life insurers start to engage in the life insurance business than vice-versa, which is in line with Section 2.1, suggesting a less volatile life insurance business.

For systemic risk measured in the non-financial system and by the approach suggested by Ergün and Girardi (2013), a similar relationship between business diversification and systemic risk is found. Interestingly, an insurer's distress seems to have an almost similar impact on the real economy approximated by the non-financial index (NoFIN) as on the financial system. It seems plausible that insurers can propagate shocks directly to the real economy, for instance, due to i) a (short-term) lack of insurance substitutability, which was a substantial systemic risk source in the cases of the two insurers AIG (2007-09) and HiH (2001), and ii) potentially reduced funding supply to the real economy by insurers (e.g. Bank of England (BoE) (2015a), European Systemic Risk Board (ESRB) (2015), Financial Stability Oversight Council (FSOC) (2013b), Bailey (2003))).

Moreover, large insurers are expected to cause significantly higher financial losses to other institutions, but leverage does not have a significant impact on insurer's systemic risk contribution, which both is in line with Weiß and Mühlnickel (2014). Non-core activities might, on average, increase systemic risk, but for the profitability stemming from the insurer's investments, no significant impact is found.

The significantly quadratic relation between systemic risk and the life ratio yields the potential for insurers to minimize their systemic risk contribution. The first order condition of the fitted regression model in Equation 9 with regard to the life ratio yields a systemic risk minimizing business allocation given by $\alpha^* = \frac{-\hat{\beta}_2}{2\hat{\beta}_1}$, which is a minimum since $\beta_1 > 0$ und $\beta_2 < 0$.

Table 5 shows the risk minimizing business allocations for all measures and sectors applied in the analysis. The risk minimizing life ratios are consistently higher than 50% life insurance, which is in line with classic portfolio theory, suggesting for the imperfectly correlated cash flows between life and non-life insurance an overweight to the less volatile life insurance business in order to reduce total risk. Thus, the regression analysis suggests that insurers can, on average, minimize systemic risk due to financial contagion stemming from their individual distress by conducting a life business allocation in the range of 54% to 59%, depending on the systemic risk measure and

ΔCoVaR$_{hist}$ (FIN). In terms of a 1% life ratio change, using $\Delta Y = -(2\hat{\beta}_1 0.99 + \hat{\beta}_2)0.0256$, yields a change of -0.0093 std ΔCoVaR$_{hist}$ (FIN).

system considered.

Systemic Risk Measure	FIN	NoFIN
ΔCoVaR$_{hist}$	0.58	0.59
ΔCoVaR$_{EG}$	0.54	0.55

Table 5: Systemic Risk minimizing Life Business Allocation

The table shows the risk minimizing allocation to life insurance based on the baseline panel regression and parameters given in Table 4.

3.4 Robustness Checks

Appendix A.6 comprises the results of several robustness checks. Table 18 contains the correlation coefficients between the independent variables of the regression model, showing only weak correlations across the explanatory variables. The regression analysis of the baseline model using unscaled regression parameters yields similar results compared to the scaled model (Table 19).

I aim to lower the potential for endogeneity in terms of reverse causality between the level of systemic risk and the insurer's contemporaneous business allocation decision by lagging the independent variables by one year (e.g. Bierth et al. (2015), Weiß and Mühlnickel (2014)). Additionally, findings by Zimmer et al. (2018), Phillips et al. (1998) and Sommer (1996) show that policyholders pay less for insurance if the insurer is subject to higher distress risk, which would actually constitute a strong monetary incentive for insurers to become diversified and a disincentive for being a monoline insurer. However, the sample consists of 52% monoline insurers that engage only in life or non-life insurance and the insurers' business allocations are overall relatively persistent over time, suggesting that the level of distress risk, and hence the resulting level of systemic risk, does not play a major role for insurer's contemporaneous business allocation decision.

I also test several different model specifications. In particular, I employ different definitions for the leverage variable (debt to equity ratio (Table 20), debt to asset ratio (Table 21)) and for the size variable (natural log of total liabilities (Table 23)), which show similar results compared to the baseline regression.

I also control for differences in the underwriting quality as suggested by Bierth et al. (2015) and Weiß and Mühlnickel (2014), since insurers with the same business mix might differ substantially in their underwriting portfolios. I implement the insurer's net claims ratio, and the regression yields similar results compared to the baseline regression (Table 22).

Moreover, the results might be biased by the extent of counterparty credit risk insurers cause. Hence, I test if insurers with strong financial linkages contribute more to systemic risk. I split the sample in subsamples consisting of insurers with the 10% highest debt to equity ratio and with the 10% lowest debt to equity ratio. For both subsamples, business diversification significantly minimizes systemic risk, and the marginal influence is relatively similar (Tables 24 and 25).

Using insurer-fixed effects reduces the significance of the results as expected due to the high persistence of the insurer's business allocation. The p-values of the baseline model with regard to the quadratic and linear terms of the $\Delta\text{CoVaR}_{hist}$ for the financial sector are 0.75 and 0.38 and of the ΔCoVaR_{EG} for the financial sector are 0.26 and 0.38.

Moreover, the results might be influenced by systematic shocks that affect multiple insurers in the system simultaneously and overlay contagion risks from an individually distressed institution to other institutions. In order to mitigate the potential influence of correlated shocks, I control for the insurer's yearly correlation with a global insurance system consisting of 382 insurers (Table 26). Controlling for correlation of an insurer with other insurers reduces as expected substantially the significance of the explanatory variables, but the results suggest that business diversification can still have a systemic risk minimizing impact despite any potentially systematic shocks.

4 Policy Implications

The findings suggest that a significant u-shaped relation between the insurer's business allocation in terms of life and non-life insurance and the insurer's systemic risk contribution in terms of financial contagion exists. More specifically, monoline life and monoline non-life insurers contribute, on average, most to systemic risk, while diversified multiline insurers with an average allocation in the range of 54% life insurance minimize the adverse consequences of their distress to other institutions. Therefore, the findings suggest that monoline insurers should be monitored more closely by supervisors than diversified multiline insurers for mitigating systemic risk in the insurance sector, as their distress results in higher contagion risks.

The extent of insurer's business diversification could also serve as an additional measure for assessing an insurer's systemic importance. It can be included in the current indicator-based model used by the IAIS for the "individual insurer monitoring" task within the holistic systemic risk framework (International Association of Insurance Supervisors (IAIS) (2019b), International Association of Insurance Supervisors (IAIS) (2018)). Taking an insurer's extent of business diversification into account could increase the precision in determining which insurers are potentially a greater threat to financial stability. For example, based on the 2016 list of global systemically important insurers (Financial Stability Board (2016)), insurers like Prudential Financial, MetLife and Aegon pose a greater threat to financial stability as they focus their business mainly on one insurance line (life insurance) compared to the other, more diversified, insurers on this list. Thus, the findings suggest that those highly focused insurers should be given special attention with regard to systemic risk.

From a macroprudential perspective, the question arises if all insurers should be incentivized to diversify their business, in particular with regard to the systemic risk minimizing allocation level. Theoretical findings by Battiston et al. (2012), Allen et al. (2012), Ibragimov et al. (2011), Beale et al. (2011) and Wagner (2010) show that risk diversification can increase the risk of a collective distress if it coincides with substantial common exposures across institutions. This relates to the second source of systemic risk in the insurance sector, which is based on common exposures across insurers (e.g. International Association of Insurance Supervisors (IAIS) (2019b), International Monetary Fund (IMF) (2016)).[16]

Against the role of common exposures for systemic risk, the findings in this paper suggest that if all insurers diversify their business, for instance in terms of the systemic risk minimizing ratio α^*, they minimize, on average, contagion risks resulting from their individual distress events that cause additional losses to other institutions in the system. Thus, for any associated impact of business diversification on common exposures, the findings show that the net impact of business diversification can be expected to reduce systemic risk in terms of financial contagion.

However, the literature provides so far no clear evidence on the levels of common exposures associated with insurance business diversification in terms of life and non-life insurance, in particular with regard to the marginal effects of business diversification on common exposures and collective distress risk across insurers. Thus, it is necessary in future research to study the exact influence of business diversification between life and non-life insurance on the extent of common exposures

[16]In that regard, the International Monetary Fund (IMF) (2016) for instance, describes systemic risk caused by financial contagion and caused by a collective distress across institutions as being not mutually exclusive.

across insurers, as business diversification, and particularly the systemic risk minimizing allocation α^*, might be associated with certain levels of common exposures that increase the risk of a collective insurer distress in case of a systematic shock.

Moreover, the potential influence of business diversification on common exposures is also relevant for the interaction of micro- and macroprudential regulation, as frameworks like Solvency II or the Global Insurance Capital Standard (ICS) typically foster business diversification at the insurer-level without considering common exposures across insurers from a macroprudential perspective (European Insurance and Occupational Pensions Authority (EIOPA) (2017)).[17]

Furthermore, the results suggest that reducing systemic risk by means of business diversification is beneficial from a regulatory perspective, but it is unclear what cost effects for insurance markets might be associated with such an extent of business diversification. For example, when considering one monoline and one multiline insurance company that have the same size, then, the monoline insurer will typically have a higher degree of diversification within its line of business, as it sells more similar insurance contracts to different policyholders compared to the multiline insurer. The larger risk pool, and hence economies of scale with respect to risk taking, enables the monoline insurer to offer a smaller premium for the same level of default risk as the multiline company (Cummins (1974)). Thus, policyholders might benefit from lower prices for a given insurance contract charged by monoline insurers compared to multiline insurers of the same size.

Moreover, multiline insurers might benefit from economies of scope, as they diversify across insurance lines which lowers their distress risk. Then, multiline insurers could charge higher premiums for insurance contracts due to lower insolvency risk compared to monoline insurers (e.g. Sommer (1996), Phillips et al. (1998), Zimmer et al. (2018)). Hence, future work should study potential market implications that might arise from an increasing level of business diversification across insurers.

[17] Solvency II and the ICS as microprudential regulatory frameworks employ a zero correlation between the solvency capital requirements for life and non-life insurance: Annex IV, Point (1) of the Directive 2009/138/EC for Solvency II and International Association of Insurance Supervisors (IAIS) (2020) for the ICS.

5 Conclusion

This research project studies the influence of business diversification between life and non-life insurance on the insurer's contribution to systemic risk in terms of financial contagion, i.e. the insurer's propensity to transmit economic shocks to other institutions.

Quantitative evidence on insurers' premium and claim cash flows associated with life and non-life insurance suggest that life insurance is less volatile compared to non-life insurance. Since cash flows from both insurance lines are mainly uncorrelated, a diversification potential for multiline insurers arises, which can significantly reduce the insurer's level of distress risk as measured by the Z-Score.

By mapping the stabilizing diversification potential between life and non-life insurance in an exemplary portfolio model, diversified insurers can reduce counterparty (credit) risk as an important channel for financial contagion and systemic risk. The model suggests a u-shaped relation between business diversification and systemic risk, and more specifically, a systemic risk minimizing allocation level with an overweight on the less volatile life insurance business.

In an empirical analysis based on a global sample of insurers, a significant u-shaped relation between business diversification and systemic risk can be confirmed. Monoline life and monoline non-life insurers contribute, on average, more to systemic risk than diversified multiline insurers. More specifically, insurers with a business allocation in the range of 54% life insurance minimize, on average, their contribution to systemic risk in terms of financial contagion.

Since business diversification between life and non-life insurance has not been taken into account so far by macroprudential insurance regulation, the findings suggest that monoline insurers should be monitored more closely than multiline insurers, since the financial distress of monoline insurers causes, on average, more severe consequences for financial stability stemming from contagion risks. Moreover, supervisors could use the extent of business diversification as an additional indicator when assessing the systemic importance of individual insurers, which could increase the precision of this determination and act as a soft incentive for insurers to diversify their business in order to increase financial stability.

A Appendix

A.1 Underwriting Cash Flows

Variables from SNL used for the cash flow analysis in Section 2.1.

i) P&C Net Premiums Earned: The GAAP Property & Casualty insurance premiums earned, net of reinsurance. This variable is used to classify non-life insurance business (Key: 286130).

ii) L&H Net Premiums Earned: Life insurance and Accident & Health premiums earned, net of reinsurance. This variable is used to classify life insurance business (Key: 286131).

iii) P&C Losses & LAE: Expenses of settling Property&Casualty insurance claims related to written policies, net of reinsurance recoverable. Expenses include those necessary for the indemnification of the insured, as well as those expenses incurred in the course of investigating and settling claims (Key: 286142).

iv) L&H Total Claims & Policy Benefits: Policy claims and benefits incurred on life and health policies, plus any interest credited to policyholder accounts and policyholder dividends on life policies. For U.S. companies, this is collected as net. For European and Asia-Pacific companies, this can be collected as gross or net (Key: 286143).

Table 6 shows the list of insurers used for the cash flow analysis between life and non-life insurance. Annual data is retrieved in US$ from 2005-2019 from SNL Financial (Market Intelligence). After cleaning for missing data, 56 insurers with a complete time series are included for the analysis.

Entity Name	Entity ID (SNL)	
1 Aflac Incorporated	103316	United States and Canada
2 Alleghany Corporation	103410	United States and Canada
3 Ambac Financial Group, Inc.	103402	United States and Canada
4 American Financial Group, Inc.	103424	United States and Canada
5 AMERISAFE, Inc.	4041394	United States and Canada
6 Ameritas Mutual Holding Company	4026711	United States and Canada
7 Arch Capital Group Ltd.	103577	United States and Canada
8 Argo Group International Holdings, Ltd.	103333	United States and Canada
9 Aspen Insurance Holdings Limited	4089391	United States and Canada
10 Assured Guaranty Ltd.	4090916	United States and Canada
11 AXIS Capital Holdings Limited	4080716	United States and Canada
12 Cincinnati Financial Corporation	103262	United States and Canada
13 Citizens, Inc.	103263	United States and Canada
14 CNO Financial Group, Inc.	4089422	United States and Canada
15 Echelon Financial Holdings Inc.	4193774	United States and Canada
16 Employers Holdings, Inc.	4142896	United States and Canada
17 Factory Mutual Insurance Company	11489	United States and Canada
18 Fairfax Financial Holdings Limited	4021790	United States and Canada
19 FedNat Holding Company	4040584	United States and Canada
20 Fidelity National Financial, Inc.	4107778	United States and Canada
21 First American Financial Corporation	103412	United States and Canada
22 Globe Life Inc.	103323	United States and Canada
23 Hanover Insurance Group, Inc.	103541	United States and Canada
24 Intact Financial Corporation	4109061	United States and Canada
25 Investors Title Company	103413	United States and Canada
26 Kansas City Life Insurance Company	103285	United States and Canada
27 Loews Corporation	103455	United States and Canada
28 Manulife Financial Corporation	4048408	United States and Canada
29 Markel Corporation	4051039	United States and Canada
30 MBIA Inc.	103405	United States and Canada
31 Mercury General Corporation	103365	United States and Canada
32 MGIC Investment Corporation	103406	United States and Canada
33 National Life Group	4048602	United States and Canada
34 New York Life Insurance Company	110248	United States and Canada
35 Principal Financial Group, Inc.	110230	United States and Canada
36 ProAssurance Corporation	4064418	United States and Canada
37 Progressive Corporation	103383	United States and Canada
38 Protective Insurance Corporation	103425	United States and Canada
39 Prudential Financial, Inc.	4072932	United States and Canada
40 Radian Group Inc.	103563	United States and Canada
41 Reinsurance Group of America, Incorporated	103450	United States and Canada
42 RenaissanceRe Holdings Ltd.	103554	United States and Canada
43 RLI Corp.	103386	United States and Canada
44 RSA Insurance Group Plc	4020890	Europe
45 Safety Insurance Group, Inc.	4074760	United States and Canada
46 Selective Insurance Group, Inc.	103451	United States and Canada
47 Stewart Information Services Corporation	103414	United States and Canada
48 The Allstate Corp.	103247	United States and Canada
49 Travelers Companies, Inc.	4055530	United States and Canada
50 Unico American Corporation	103550	United States and Canada
51 United Fire Group, Inc.	103396	United States and Canada
52 Universal Insurance Holdings, Inc.	4040161	United States and Canada
53 Unum Group	103324	United States and Canada
54 UTG, Inc.	103307	United States and Canada
55 W. R. Berkley Corporation	103336	United States and Canada
56 White Mountains Insurance Group, Ltd.	4050763	United States and Canada

Table 6: Insurer Sample for the Cash Flow Analysis

A.2 Z-Score Analysis between Diversified and Undiversified Insurers

The Z-Score is a well-established measure for the default risk of an individual institution (e.g. Shim (2017a), Köhler (2015), Laeven and Levine (2009), Stiroh and Rumble (2006)). I use yearly accounting data from SNL Financial (S&P Market Intelligence) for the analysis in Section 2.1 and all data is retrieved in US$ in order to mitigate currency bias. It is defined as

$$Z - Score_{i,t} = \frac{RoA_{i,t} + CAR_{i,t}}{Std(RoA)_{i,t}} \tag{10}$$

where $Z - Score_{i,t}$ means the Z-Score of institution i in year y, $RoA_{i,t}$ denotes the return on assets (RoA) of institution i in year t, which is calculated as net income before taxes (EBT) divided by total assets, $CAR_{i,t}$ denotes the capital-to-asset ratio of institution i in year t, which is calculated as the ratio of total equity to total assets. $Std(RoA)_{i,t}$ corresponds to the standard deviation of the return on assets based on a three-year rolling window approach. For instance, Shim (2017a) uses a 5-year rolling window. I follow Köhler (2015) and winsorize the variables at the 1- and 99-percentile level.

SNL variable keys used for the required accounting data:

- Total Assets: 275617
- Total Equity: 275619
- Net Income Before Tax (EBT): 275854 (SP_EBT)

The following Tables show the insurers included in the monoline sample, and the insurers included in the multiline sample.

Entity Name	Entity ID (SNL)	Geography
1 1347 Property Insurance Holdings, Inc.	4380081	United States and Canada
2 Admiral Group Plc	4147411	Europe
3 ADRIATIC osiguranje d.d.	4194083	Europe
4 Aflac Incorporated	103316	United States and Canada
5 AIA Group Ltd.	4252473	Asia-Pacific
6 Aksigorta AS	4173978	Europe
7 Al Ain Ahlia Insurance Company PSC	4173984	Middle East
8 AL Dhafra Insurance Company P.S.C.	4173986	Middle East
9 Al Madina Insurance Company SAOG	4323460	Middle East
10 Al Rajhi Company for Cooperative Insurance	4581733	Middle East
11 Al Sagr National Insurance Company PSC	4173996	Middle East
12 Al Wathba National Insurance Company PJSC	4185095	Middle East
13 Alleghany Corporation	103410	United States and Canada
14 Ambac Financial Group, Inc.	103402	United States and Canada
15 American Financial Group, Inc.	103424	United States and Canada
16 American Overseas Group Limited	4114845	United States and Canada
17 AMERISAFE, Inc.	4041394	United States and Canada
18 Anicom Holdings, Inc.	4331395	Asia-Pacific
19 Arabia Insurance Cooperative Company	4654974	Middle East
20 Arabian Shield Cooperative Insurance Company	4380702	Middle East
21 Arch Capital Group Ltd.	103577	United States and Canada
22 Argo Group International Holdings, Ltd.	103333	United States and Canada
23 Assured Guaranty Ltd.	4090916	United States and Canada
24 Atlantic Insurance Company Public Ltd.	4328600	Europe
25 Atlas Financial Holdings, Inc.	4259592	United States and Canada
26 AXA Cooperative Insurance Company	4376644	Middle East
27 AXA Equitable Holdings, Inc.	9170810	United States and Canada
28 AXIS Capital Holdings Limited	4080716	United States and Canada
29 Bangkok Insurance PCL	4174503	Asia-Pacific
30 Bangkok Life Assurance PCL	4327093	Asia-Pacific
31 Bao Minh Insurance Corporation	4340522	Asia-Pacific
32 Beazley Plc	4096135	Europe
33 Blue Capital Reinsurance Holdings Ltd.	4414216	United States and Canada
34 Brighthouse Financial, Inc.	6588911	United States and Canada
35 Bupa Arabia For Cooperative Insurance Company	4410248	Middle East
36 Chesnara Plc	4185820	Europe
37 China Life Insurance Co. Ltd.	4175229	Asia-Pacific
38 CIG Pannónia Életbiztosító Nyrt.	4376760	Europe
39 Cincinnati Financial Corporation	103262	United States and Canada
40 Citizens, Inc.	103263	United States and Canada
41 CNO Financial Group, Inc.	4089422	United States and Canada
42 Coface SA	4203970	Europe
43 Company for Cooperative Insurance	4179036	Middle East
45 Dhipaya Insurance PCL	4175895	Asia-Pacific
46 Dhofar Insurance Company (S.A.O.G)	4175896	Middle East
47 Direct Line Insurance Group Plc	4335522	Europe
48 Discovery Ltd.	4182896	Africa
49 Doha Insurance Group Q.P.S.C.	4197632	Middle East
50 Dubai National Insurance & Reinsurance (P.S.C.)	4197740	Middle East
51 Echelon Financial Holdings Inc.	4193774	United States and Canada
52 Emirates Insurance Company PJSC	4176119	Middle East
53 Employers Holdings, Inc.	4142896	United States and Canada
54 Essent Group Ltd.	4243335	United States and Canada
55 Fairfax Financial Holdings Limited	4021790	United States and Canada
56 FBD Holdings Plc	4182724	Europe
57 FedNat Holding Company	4040584	United States and Canada
58 Fidelity National Financial, Inc.	4107778	United States and Canada
59 First Acceptance Corporation	102966	United States and Canada
60 First American Financial Corporation	103412	United States and Canada
61 First Insurance Co. Ltd.	4176397	Asia-Pacific
62 GAINSCO, INC.	103352	United States and Canada
63 Globe Life Inc.	103323	United States and Canada
64 Günes Sigorta AS	4176902	Europe
65 Hallmark Financial Services, Inc.	103415	United States and Canada
66 Hanover Insurance Group, Inc.	103541	United States and Canada
67 Hanwha Life Insurance Co., Ltd.	4177711	Asia-Pacific
68 HCI Group, Inc.	4189837	United States and Canada
69 Heungkuk Fire & Marine Insurance Co., Ltd.	4177716	Asia-Pacific

Table 7: List of all 165 Monoline Insurers for the Z-Score Analysis from 2003-2018. Part 1

Entity Name	Entity ID (SNL)	Geography
70 Hiscox Ltd.	4089191	United States and Canada
71 Hyundai Marine & Fire Insurance Co., Ltd.	4053701	Asia-Pacific
72 ICC Holdings, Inc.	4834672	United States and Canada
73 Insurance Australia Group Ltd.	4183836	Asia-Pacific
74 Intact Financial Corporation	4109061	United States and Canada
75 Investors Title Company	103413	United States and Canada
76 James River Group Holdings, Ltd.	4188850	United States and Canada
77 Jordan French Insurance Company (Plc)	4177561	Middle East
78 Just Group Plc	4420887	Europe
79 Kansas City Life Insurance Company	103285	United States and Canada
80 Kinsale Capital Group, Inc.	4252831	United States and Canada
81 Lancashire Holdings Ltd.	4111293	United States and Canada
82 Legal & General Group Plc	4145053	Europe
83 Loews Corporation	103455	United States and Canada
84 Lotte Insurance Co., Ltd.	4175764	Asia-Pacific
85 Maiden Holdings, Ltd.	4165352	United States and Canada
86 Malath Cooperative Insurance Company	4259112	Middle East
87 Manulife Financial Corporation	4048408	United States and Canada
88 Markel Corporation	4051039	United States and Canada
89 MBIA Inc.	103405	United States and Canada
90 Medibank Private Ltd.	4160656	Asia-Pacific
91 Mercuries Life Insurance Co.	4178540	Asia-Pacific
92 Mercury General Corporation	103365	United States and Canada
93 Methaq Takaful Insurance Company PSC	4622733	Middle East
94 MGIC Investment Corporation	103406	United States and Canada
95 Mirae Asset Life Insurance Co., Ltd.	4180662	Asia-Pacific
96 National General Holdings Corporation	4243865	United States and Canada
97 NEM Insurance Plc	4194447	Africa
98 New China Life Ins Co. Ltd.	4329576	Asia-Pacific
99 New India Assurance Company Ltd.	4138524	Asia-Pacific
100 Nib Holdings Ltd.	4327089	Asia-Pacific
101 NMI Holdings, Inc.	4333424	United States and Canada
102 Palomar Holdings, Inc.	14420758	United States and Canada
103 Personal Group Holdings Plc	4145311	Europe
104 Petrolimex Insurance Corporation	4195446	Asia-Pacific
105 Phoenix Group Holdings Plc	4307393	Europe
106 Primerica, Inc.	4245322	United States and Canada
107 Principal Financial Group, Inc.	110230	United States and Canada
108 ProAssurance Corporation	4064418	United States and Canada
109 Progressive Corporation	103383	United States and Canada
110 ProSight Global, Inc.	4282517	United States and Canada
111 Protective Insurance Corporation	103425	United States and Canada
112 Protector Forsikring ASA	4248064	Europe
113 Prudential Financial, Inc.	4072932	United States and Canada
114 Prudential Plc	4023122	Europe
115 PT Paninvest Tbk	4179828	Asia-Pacific
116 PVI Holdings	4619142	Asia-Pacific
117 Qatar General Insurance & Reinsurance Company Q.P.S.C.	4179847	Middle East
118 QBE Insurance Group Ltd.	4021467	Asia-Pacific
119 Radian Group Inc.	103563	United States and Canada
120 Rand Merchant Investment Holdings Ltd.	4323601	Africa
121 Reinsurance Group of America, Incorporated	103450	United States and Canada
122 RenaissanceRe Holdings Ltd.	103554	United States and Canada
123 RLI Corp.	103386	United States and Canada
124 RSA Insurance Group Plc	4020890	Europe
125 Sabre Insurance Group plc	9168692	Europe
126 Safety Insurance Group, Inc.	4074760	United States and Canada
127 Saga Plc	4538740	Europe
128 Samsung Life Insurance Co., Ltd.	4111916	Asia-Pacific
129 Saudi Arabian Cooperative Insurance Company	4259093	Middle East
130 Saudi Re for Cooperative Reinsurance Company	4382619	Middle East
131 Selective Insurance Group, Inc.	103451	United States and Canada
132 Shinkong Insurance Co. Ltd.	4326292	Asia-Pacific
133 Singapore Reinsurance Corporation Ltd.	4180647	Asia-Pacific
134 Sirius International Insurance Group, Ltd.	4199335	United States and Canada
135 Société Tunisienne d'Assurances et de Réassurances	4436844	Africa
136 Société Tunisienne de Réassurance	4180714	Africa
137 Stewart Information Services Corporation	103414	United States and Canada
138 Storebrand ASA	4144815	Europe
139 Suncorp Group Ltd.	4310504	Asia-Pacific

Table 8: List of all 165 Monoline Insurers for the Z-Score Analysis from 2003-2018. Part 2

Entity Name	Entity ID (SNL)	Geography
140 Swiss Life Holding AG	4144859	Europe
141 Syn Mun Kong Insurance PCL	4331428	Asia-Pacific
142 Syncora Holdings Ltd.	4121642	United States and Canada
143 Thai Reinsurance PCL	4181144	Asia-Pacific
144 The Allstate Corp.	103247	United States and Canada
145 Third Point Reinsurance Ltd.	4316478	United States and Canada
146 Travelers Companies, Inc.	4055530	United States and Canada
147 Trisura Group Ltd.	6676307	United States and Canada
148 Trupanion, Inc.	4202601	United States and Canada
149 Tryggingamiðstöðin hf.	4181394	Europe
150 TW Fire & Marine Ins Co. Ltd.	4181059	Asia-Pacific
151 Unico American Corporation	103550	United States and Canada
152 Union Insurance Co. Ltd.	4181480	Asia-Pacific
153 United Cooperative Assurance Company	4436925	Middle East
154 United Fire Group, Inc.	103396	United States and Canada
155 United Insurance Holdings Corp.	4169946	United States and Canada
156 Universal Insurance Holdings, Inc.	4040161	United States and Canada
157 Unum Group	103324	United States and Canada
158 UTG, Inc.	103307	United States and Canada
159 Vátryggingafélag Íslands hf.	4181583	Europe
160 Vietnam National Reinsurance Corporation	4181631	Asia-Pacific
161 Voya Financial, Inc.	4041737	United States and Canada
162 W. R. Berkley Corporation	103336	United States and Canada
163 Walaa Cooperative Insurance Company	4180378	Middle East
164 Watford Holdings Ltd.	4637500	United States and Canada
165 White Mountains Insurance Group, Ltd.	4050763	United States and Canada

Table 9: List of all 165 Monoline Insurers for the Z-Score Analysis from 2003-2018. Part 3

Entity Name	Entity ID (SNL)	Geography
1 Abu Dhabi National Insurance Company PJSC	4173862	Middle East
2 Abu Dhabi National Takaful Company PSC	4207011	Middle East
3 AEGON N.V.	113920	Europe
4 Ageas SA/NV	4022946	Europe
5 AIICO Insurance Plc	4287418	Africa
6 Al Ahleia Insurance Company S.A.K.P.	4173980	Middle East
7 Al Buhaira National Insurance Company PSC	4193192	Middle East
8 Al Khaleej Takaful Insurance Company Q.P.S.C.	4616783	Middle East
9 Allianz - Slovenská poistovna, a. s.	4193227	Europe
10 Allianz Saudi Fransi Cooperative Insurance Company	4257183	Middle East
11 American International Group, Inc.	103330	United States and Canada
12 American National Insurance Company	103423	United States and Canada
13 Arab Insurance Group (B.S.C.)	4164281	Middle East
14 ASR Nederland NV	4256877	Europe
15 Assicurazioni Generali SpA	4049198	Europe
16 Assurant, Inc.	4090153	United States and Canada
17 Atlantic American Corporation	103256	United States and Canada
18 Aviva Plc	4021316	Europe
19 AvivaSA Emeklilik ve Hayat AS	4376325	Europe
20 AXA SA	4009223	Europe
21 Bahrain National Holding Company BSC	4212307	Middle East
22 Bâloise Holding AG	4023439	Europe
23 Bao Viet Holdings	4185141	Asia-Pacific
24 Britam Holdings Plc	4433862	Africa
25 Central Reinsurance Corp.	4147441	Asia-Pacific
26 China Pacific Insurance (Group) Co., Ltd.	4175233	Asia-Pacific
27 China Reinsurance (Grp) Corp.	4175234	Asia-Pacific
28 Chubb Limited	103417	Europe
29 Clal Insurance Enterprises Holdings Ltd.	4147726	Middle East
30 Custodian Investment Plc	4198001	Africa
31 DB Insurance Co., Ltd.	4170271	Asia-Pacific
32 Delta Insurance Company	4175853	Middle East
33 E-L Financial Corporation Limited	4109059	United States and Canada
34 European Reliance General Insurance Company SA	4232593	Europe
35 FBL Financial Group, Inc.	103687	United States and Canada
36 First Takaful Insurance Company - KPSC	4186943	Middle East
37 General Insurance Corporation of India	4176633	Asia-Pacific
38 Genworth Financial, Inc.	4091160	United States and Canada
39 Grupo Catalana Occidente, SA	4248034	Europe
40 Gulf Insurance Group K.S.C.P.	4176892	Middle East
41 Harel Insurance Investments & Financial Services Ltd.	4215838	Middle East
42 Hartford Financial Services Group, Inc.	103647	United States and Canada
43 Helvetia Holding AG	4252499	Europe
44 Horace Mann Educators Corporation	103363	United States and Canada
45 I.D.I. Insurance Company Ltd.	4177397	Middle East
46 Islamic Arab Insurance Co. (Salama) PJSC	4217710	Middle East
47 Islamic Insurance Co. (PSC)	4589837	Middle East
48 Jubilee Holdings Ltd.	4177576	Africa
49 Kemper Corporation	103308	United States and Canada

Table 10: List of all 91 Multiline Insurers for the Z-Score Analysis from 2003-2018. Part 1

Entity Name	Entity ID (SNL)	Geography
50 Kenya Reinsurance Corporation Ltd.	4616999	Africa
51 Korean Reinsurance Company	4143198	Asia-Pacific
52 Kuwait Insurance Company S.A.K.P	4177729	Middle East
53 Lincoln National Corporation	103362	United States and Canada
54 Menora Mivtachim Holdings Ltd.	4551337	Middle East
55 MetLife, Inc.	4051708	United States and Canada
56 Münchener Rückversicherungs-Gesellschaft AG	4005715	Europe
57 Mutual Benefits Assurance Plc	4617002	Africa
58 National General Insurance Co. (PJSC)	4197755	Middle East
59 National Reinsurance Corporation of the Philippines	4179068	Asia-Pacific
60 National Security Group, Inc.	103293	United States and Canada
61 National Western Life Group, Inc.	4633670	United States and Canada
62 Niger Insurance Plc	4632433	Africa
63 NN Group NV	4168063	Europe
64 NÜRNBERGER Beteiligungs-AG	4145343	Europe
65 Oman United Insurance Company SAOG	4194821	Middle East
66 People's Insurance Company (Group) of China Ltd.	4179562	Asia-Pacific
67 Phoenix Holdings Ltd.	4177399	Middle East
68 Ping An Ins (Grp) Co of CN Ltd	4179619	Asia-Pacific
69 Powszechny Zaklad Ubezpieczen SA	4185178	Europe
70 Pozavarovalnica Sava, d.d.	4180379	Europe
71 Qatar Insurance Company Q.S.P.C.	4179848	Middle East
72 Qatar Islamic Insurance Group (Q.P.S.C.)	4196319	Middle East
73 RheinLand Holding AG	4376155	Europe
74 Royal Exchange Plc	4617004	Africa
75 Sampo Oyj	4145129	Europe
76 Samsung Fire & Marine Insurance Co., Ltd.	4324105	Asia-Pacific
77 SCOR SE	4020905	Europe
78 Società Cattolica di Assicurazione - SC	4180808	Europe
79 Sun Life Financial Inc.	4057252	United States and Canada
80 Swiss Re AG	4290308	Europe
81 Tiptree Inc.	4426760	United States and Canada
82 Topdanmark A/S	4139750	Europe
83 Triple-S Management Corporation	4074762	United States and Canada
84 Union Insurance Company PJSC	4616998	Middle East
85 Unipol Gruppo SpA	4145340	Europe
86 UNIQA Insurance Group AG	4145031	Europe
87 Vaudoise Assurances Holding SA	4248072	Europe
88 Wafa Assurance SA	4203786	Africa
89 Wüstenrot & Württembergische AG	4181907	Europe
90 Zavarovalnica Triglav, d.d.	4194691	Europe
91 Zurich Insurance Group AG	4042156	Europe

Table 11: List of all 91 Multiline Insurers for the Z-Score Analysis from 2003-2018. Part 2

A.3 The Counterparty's Expected Loss

The total free cash flow R of the insurance holding is given by

$$R = \alpha\, R_L + (1-\alpha)\, R_{NL}. \tag{11}$$

where R_L and R_{NL} denote the normally distributed equity cash flows generated by the life and non-life insurance subsidiaries.

Since it is assumed for illustrative reasons that the equity cash flows from the life and non-life insurance business have a similar expectation, the holding's expected total cash flow is independent from α. The first order condition of the counterparty's expected loss (Equation 2) with regard to the business allocation parameter α yields

$$\begin{aligned}
\frac{\partial EL}{\partial \alpha} &= (D-\mu_R)\,\frac{\partial \Phi(z)}{\partial \alpha} + \frac{\partial \sigma_R}{\partial \alpha}\,\Phi'(z) + \sigma_R\,\frac{\partial \Phi'(z)}{\partial \alpha} \\
&= (D-\mu_R)\,\Phi'(z)\,\frac{\partial z}{\partial \alpha} + \frac{1}{2\sigma_R}\,\frac{\partial \sigma_R^2}{\partial \alpha}\,\Phi'(z) - \sigma_R\, z\,\Phi'(z)\,\frac{\partial z}{\partial \alpha} \\
&= \frac{1}{2\sigma_R}\,\Phi'(z)\,\frac{\partial \sigma_R^2}{\partial \alpha}
\end{aligned} \tag{12}$$

Since $\sigma_R > 0$ and $\Phi'(z) > 0$, the critical point of the expected loss is given by the minimum variance allocation. The critical point yields a positive second order condition for a sufficiently small correlation between both insurance lines, which is in line with the low correlation levels as suggested in Section 2, leading to a risk minimum. Hence, the risk minimizing allocation is given by

$$\begin{aligned}
\frac{\partial \sigma_R^2}{\partial \alpha} &= 0 \\
\alpha^* &= \frac{\sigma_{NL}^2 - \sigma_L\,\sigma_{NL}\,\rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\,\sigma_L\,\sigma_{NL}\,\rho}
\end{aligned} \tag{13}$$

Note:

$$z = \frac{D - \mu_R}{\sigma_R}$$

$$\frac{\partial \sigma_R}{\partial \alpha} = \frac{\partial (\sigma_R^2)^{1/2}}{\partial \alpha} = \frac{1}{2\sigma_R}\frac{\partial \sigma_R^2}{\partial \alpha}$$

$$\frac{\partial \Phi(z)}{\partial \alpha} = \Phi'(z)\frac{\partial z}{\partial \alpha}$$

$$\frac{\partial \Phi'(z)}{\partial \alpha} = -z\Phi'(z)\frac{\partial z}{\partial \alpha}$$

A.4 The Systems used for the Systemic Risk Measures

The Global Financial System (FIN)

I estimate for each institution a separate return index of the financial system, based on a market capitalization weighted simple return index of all other institutions in the system. Hence, it prevents from a double counting of the specific institution's return and a potentially constructed correlation between the institution's tail risk and the system's tail risk.

Similar to Bisias et al. (2012), the index return series is calculated as follows: MC_t^i stands for the market capitalization of institution i at time t in US\$. P_t^i denotes insurer i's stock price in US\$. The system is given by a subset $S \subseteq \{1, ..., N\}$, where N is the number of all institutions in the system. Then, the return of the index for system S excluding firm $i \in \{1, ..., N\}$ at time t is given as the market capitalization weighted average of the remaining institutions' returns from time $t-1$ to t:

$$r_t^{S|i} = \sum_{s \in S \setminus \{i\}} \frac{MC_{t-1}^s}{\sum_{j \in S \setminus \{i\}} MC_{t-1}^j} \left(\frac{P_t^s}{P_{t-1}^s} - 1\right) \tag{14}$$

In the index for the global financial system (FIN), all financial firms in Datastream are included that 1) exhibit more than 1500 observations of the total return during the whole considered period to ensure sufficient liquidity and consistency of the data, and 2) are either alive in 2016 or dead in 2016, but listed in the previous period in one of the five largest global markets (United States, Germany, United Kingdom, China, and Japan).[18] The number and institutional types used to

[18] This restriction is intended to narrow down the resulting amount of data.

construct the resulting index (FIN) is shown in Table 12.

Fraction of Banks	Fraction of Brokers	Fraction of Insurers	Fraction of Real Estate Firms	Absolute Number of Firms	Total Market Cap. (trillion USD)	Time Period
40.1%	21.8%	15.2%	22.4%	954	4.42	2004
39.7%	22.3%	15%	22.6%	1053	5.09	2005
38.2%	22.7%	14.2%	24.5%	1122	5.84	2006
37.6%	23.1%	14.1%	24.9%	1187	7.55	2007
37.4%	23.3%	14.1%	24.8%	1204	7.58	2008
37.4%	23.1%	14.2%	25%	1226	7.72	2009
36.8%	23%	14.4%	25.4%	1254	8.22	2010
36.7%	23%	14.3%	25.7%	1270	8.53	2011
36.7%	23%	14.2%	25.6%	1272	8.67	2012
36.7%	23%	14.2%	25.6%	1272	8.85	2013
36.7%	23%	14.2%	25.6%	1272	8.95	2014
36.7%	23%	14.2%	25.6%	1272	9.36	2015
36.7%	23%	14.2%	25.6%	1272	9.87	2016
36.7%	23%	14.2%	25.6%	1272	10.48	2017

Table 12: Number and Institutional Types in the Global Financial System (FIN)

An institution is classified as bank (i.e. commercial bank, or depository firm) if its SIC code is 6021, 6022, 6029, 6035, 6036, 6061, 6062, 6081, or 6082, broker (i.e. non-depository credit firm, investment bank, or security and commodity broker) if its SIC code is between 6100 and 6280, insurer (i.e., insurance carrier) if its SIC code is between 6300 and 6400, or as real estate firm (i.e. real estate property operators, developer, agents, or managers) if its SIC code is between 6500 and 6600.

The Global Non-Financial System (NoFIN)

Data for the global non-financial (NoFIN) index is retrieved from Datastream and includes 5210 international non-financial firms (in 2018) from a broad spectrum of industrial sectors and geographical regions. Table 13 gives an overview of the geographic and sectoral distribution of firms within the index.

Geographic Distribution		**Sector Distribution**	
Country	Proportion	Sector	Proportion
Japan	16%	Food Products	4%
U.S.	15%	Industrial Machinery	4%
United Kingdom	6%	Pharmaceuticals	3%
Germany	4%	Con. Electricity	3%
France	4%	Heavy Construction	3%
Canada	4%	Building Mat. & Fix.	3%
India	3%	Specialty Chemicals	3%
Hong Kong	2%	Software	2%
South Korea	2%	Exploration & Prod.	2%
Switzerland	2%	Semiconductors	2%

Table 13: Composition of the NoFIN System

Relative weight of different countries and industrial sectors in the Datastream World Non-Financial Index (NoFIN) as of January 2018.

A.5 Variables and Data for the Regression Analysis

Table 14 gives an overview of the variables and data used for the baseline regression.

Variable name	Definition	Data source
Dependent variables		
ΔCoVaR	Difference between a system's Value-at-Risk (VaR) conditional on an insurer being in distress at the 5% quantile and the system's VaR conditional on the firm's benchmark state.	Datastream
Explanatory variables		
Life	Ratio of net premiums earned in life-health business to total net premiums earned. It is net of reinsurance.	SNL Key: 132544, 286131; ORBIS
Size	Natural logarithm of total assets.	SNL Key: 132264, SP_TOT_ASSETS
Leverage	Ratio of total net premiums earned to ph surplus (total assets minus total liabilities).	SNL Key: 132541, 132544, 263008, 132264, SP_TOT_ASSETS, 263009, SNL_TOT_LIAB
Non-Core Act.	Ratio of total liabilities to total insurance reserves.	SNL Key: 263009, SNL_TOTAL_LIAB, 263004, SNL_TOTAL_GROSS_INS_RESV
RoI	Ratio of absolute investment income to total assets.	SNL Key: 245211, SNL_INSURANCE_TOT_ROI, 132264, SP_TOT_ASSETS

Table 14: Variable Definitions and Data Sources used in the Baseline Regression Analysis

I collect data mainly from SNL Financial (S&P Market Intelligence). If the first SNL key does not provide sufficient data for a given variable, a different key for the same variable in SNL was used. Missing data is also added from Datastream and ORBIS (life premiums) by means of ISIN matches. Data is retrieved in US$.

The following tables (15, 16) show the distribution of institution types and geographic regions of the insurers in the sample.

Classification	Fraction
Multiline	48.04%
Non-Life Insurer	31.37%
Life Insurer	20.59%

Table 15: Institutional Types of the 102 Insurers in the Baseline Regression Sample

Geography	Fraction
Europe	42.16%
United States and Canada	34.31%
Asia-Pacific	12.75%
Middle East	6.86%
Africa	3.92%

Table 16: The Geographic Distribution of the 102 Insurers in the Baseline Regression Sample

Table 17 shows all insurers included in the panel regressions.

Name	ISIN	Name	ISIN
1 Admiral Group Plc	GB00B02J6398	52 Intact Financial Corporation	CA45823T1066
2 AEGON N.V.	NL0000303709	53 ADRIATIC osiguranje d.d.	HRJDOSRA0001
3 Aflac Incorporated	US0010551028	54 Lancashire Holdings Ltd.	BMG5361W1047
4 AIA Group Ltd.	HK0000069689	55 Liberty Holdings	ZAE000127148
5 Al Khaleej Takaful Insurance Company Q.P.S.C.	QA0006929762	56 Loews Corporation	US5404241086
6 Alleghany Corporation	US0171751003	57 Manulife Financial Corporation	CA56501R1064
7 The Allstate Corp.	US0200021014	58 Mapfre	ES0124244E34
8 Alm Brand	DK0015250344	59 Mapfre Middlesea	MT0000050105
9 American International Group Inc.	US0268747849	60 Markel Corporation	US5705351048
10 Anadolu Hayat Emeklilik	TRAANHYT91O3	61 Menora Mivtachim Holdings Ltd.	IL0005660183
11 Arch Capital Group Ltd.	BMG0450A1053	62 Meritz Fire & Mar.In.	KR7000060004
12 Assicurazioni Generali SpA	IT0000062072	63 MetLife Inc.	US59156R1086
13 Assurant Inc.	US04621X1081	64 MGIC Investment Corporation	US5528481030
14 Assured Guaranty Ltd.	BMG0585R1060	65 Migdal Insurance	IL0010811656
15 Atlanta	MA0000011710	66 Phoenix Holdings Ltd.	IL0007670123
16 Atlantic Insurance Company Public Ltd.	CY0006010314	67 Picc Property & Clty.'H'	CNE100000593
17 Aviva Plc	GB0002162385	68 Ping An Insurance (Group) Company of China Ltd.	CNE1000003X6
18 AXA SA	FR0000120628	69 Pozavarovalnica Sava d.d.	SI0021110513
19 AXIS Capital Holdings Limited	BMG0692U1099	70 Principal Finl.Gp.	US74251V1026
20 Bâloise Holding AG	CH0012410517	71 Progressive Ohio	US7433151039
21 Bangkok Life Assurance PCL	TH1016010007	72 Protector Forsikring ASA	NO0010209331
22 Beazley Plc	GB00BYQ0JC66	73 Prudential Finl.	US7443201022
23 Societa Cattolica di Assicurazione - Societa Cooperativa	IT0000784154	74 Powszechny Zaklad Ubezpieczen SA	PLPZU0000011
24 Chesnara Plc	GB00B00FPT80	75 Qatar Insurance Company Q.S.P.C.	QA0006929838
25 China Life Insurance Co. Ltd.	TW0002823002	76 Radian Group Inc.	US7502361014
26 China Life Insurance 'H'	CNE1000002L3	77 Reinsurance Group of America Incorporated	US7593516047
27 China Taiping In.Hdg.	HK0000055878	78 RenaissanceRe Holdings Ltd.	BMG7496G1033
28 Chubb Limited	CH0044328745	79 RSA Insurance Group Plc	GB00BKKMKR23
29 Cincinnati Financial Corporation	US1720621010	80 Sampo Oyj	FI0009003305
30 Clal Insurance Enterprises Holdings Ltd.	IL0002240146	81 Samsung Fire & Marine Insurance Co. Ltd.	KR7000810002
31 Cna Financial	US1261171003	82 SCOR SE	FR0010411983
32 CNO Financial Group Inc.	US12621E1038	83 St.James'S Place	GB0007669376
33 Croatia Osiguranje	HRCROSRA0002	84 Storebrand ASA	NO0003053605
34 DB Insurance Co. Ltd.	KR7005830005	85 Suncorp Group Ltd.	AU000000SUN6
35 Discovery	ZAE000022331	86 Swiss Life Holding AG	CH0014852781
36 E-L Financial Corporation Limited	CA2685751075	87 Swiss Re AG	CH0126881561
37 European Reliance General Insurance Company SA	GRS277023008	88 Topdanmark A/S	DK0060477503
38 Fairfax Financial Holdings Limited	CA3039011026	89 Torchmark	US8910271043
39 FBD Holdings Plc	IE0003290289	90 Travelers Cos.	US89417E1091
40 Fidelity National Financial Inc.	US31620R3030	91 Tryg	DK0060636678
41 First American Financial Corporation	US31847R1023	92 Unipol Gruppo SpA	IT0004810054
42 Genworth Mi Canada	CA37252B1022	93 Unipolsai	IT0004827447
43 Gjensidige Forsikring	NO0010582521	94 UNIQA Insurance Group AG	AT0000821103
44 Globalcapital	MT0000170101	95 Unum Group	US91529Y1064
45 Great Eastern Hdg.	SG1I55882803	96 Vaudoise Assurances Holding SA	CH0021545667
46 Grupo Catalana Occidente SA	ES0116920333	97 Vienna Insurance Group A	AT0000908504
47 Hannover Ruck.	DE0008402215	98 W. R. Berkley Corporation	US0844231029
48 Hanover Insurance Group Inc.	US4108671052	99 Wafa Assurance SA	MA0000010928
49 Harel Insurance Investments & Financial Services Ltd.	IL0005850180	100 Wüstenrot & Württembergische AG	DE0008051004
50 Hartford Financial Services Group Inc.	US4165151048	101 Zavarovalnica Triglav d.d.	SI0021111651
51 Insurance Australia Group Ltd.	AU000000IAG3	102 Zurich Insurance Group AG	CH0011075394

Table 17: List of all Insurers for the Baseline Regression from 2004-2017

A.6 Robustness Checks: Supplementary Tables

Table 18 shows the correlation coefficients of the variables used in the baseline panel regression.

Life	Total Assets	Leverage	Non-Core Act.	RoI
1	0.32	0.13	0.17	0.19
	1	0.04	0.04	0.08
		1	-0.12	-0.06
			1	0.15
				1

Table 18: Correlation Coefficients of the Explanatory Variables in the Baseline Regression

The table shows the correlation coefficients for the regression model in Equation 9 based on the explanatory variables used in Table 4.

The following tables show the outcomes of several robustness checks.

	Dependent variable:			
	ΔCoVaR$_{hist}$ (FIN)	ΔCoVaR$_{hist}$ (NoFIN)	ΔCoVaR$_{EG}$ (FIN)	ΔCoVaR$_{EG}$ (NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	0.016***	0.011*	0.006**	0.004**
	$p = 0.007$	$p = 0.067$	$p = 0.018$	$p = 0.014$
$Life$	−0.019***	−0.013**	−0.006**	−0.005**
	$p = 0.006$	$p = 0.049$	$p = 0.017$	$p = 0.012$
$Total\ Assets$	0.003***	0.002***	0.001***	0.001***
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$Leverage$	0.001	0.001	0.0002	0.0001
	$p = 0.153$	$p = 0.110$	$p = 0.298$	$p = 0.320$
$Non-Core\ Act.$	0.00001**	0.00001	0.000	0.00000
	$p = 0.011$	$p = 0.167$	$p = 0.993$	$p = 0.930$
RoI	0.003	0.001	0.002	0.001
	$p = 0.766$	$p = 0.910$	$p = 0.686$	$p = 0.638$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	941	941	941	941
R^2	0.836	0.803	0.821	0.807
Adjusted R^2	0.832	0.798	0.817	0.802
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 19: OLS Panel Regression: Baseline Model with Unscaled Parameters

The table shows the results of the OLS panel regression as in Table 4, but with unscaled parameters. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ (FIN) and (NoFIN) refers to the CoVaR measure on historical quantiles w.r.t. the global financial and non-financial system. ΔCoVaR$_{EG}$ (FIN) and (NoFIN) refers to the same systems, but use the estimation technique by Ergün and Girardi (2013).

	Dependent variable:			
	ΔCoVaR$_{hist}$ (FIN)	ΔCoVaR$_{hist}$ (NoFIN)	ΔCoVaR$_{EG}$ (FIN)	ΔCoVaR$_{EG}$ (NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	0.370**	0.256	0.360**	0.372**
	$p = 0.027$	$p = 0.176$	$p = 0.048$	$p = 0.040$
$Life$	−0.436**	−0.314	−0.392**	−0.412**
	$p = 0.020$	$p = 0.129$	$p = 0.045$	$p = 0.034$
$Total\ Assets$	0.345***	0.353***	0.497***	0.522***
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$Leverage: D/E$	−0.030	−0.034	−0.098**	−0.093*
	$p = 0.489$	$p = 0.434$	$p = 0.043$	$p = 0.055$
$Non - Core\ Act.$	0.024**	0.014	−0.006	−0.005
	$p = 0.032$	$p = 0.341$	$p = 0.500$	$p = 0.657$
RoI	0.004	−0.0002	0.008	0.010
	$p = 0.855$	$p = 0.994$	$p = 0.695$	$p = 0.649$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	941	941	941	941
R^2	0.835	0.802	0.829	0.814
Adjusted R^2	0.831	0.797	0.825	0.809
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 20: OLS Panel Regression: Leverage as D/E Ratio

The table shows the results of the OLS panel regression as in Table 4, but defines leverage as the debt/equity ratio. All panel regressions are estimated with year and geographic fixed effects and clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ (FIN) and (NoFIN) refers to the CoVaR measure on historical quantiles w.r.t. the global financial and non-financial system. ΔCoVaR$_{EG}$ (FIN) and (NoFIN) refers to the same systems, but use the estimation technique by Ergün and Girardi (2013). Regression parameters are standardized with mean 0 and st. dev. of 1.

	Dependent variable:			
	ΔCoVaR$_{hist}$ (FIN)	ΔCoVaR$_{hist}$ (NoFIN)	ΔCoVaR$_{EG}$ (FIN)	ΔCoVaR$_{EG}$ (NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	0.385**	0.272	0.397**	0.410**
	$p = 0.021$	$p = 0.150$	$p = 0.032$	$p = 0.026$
$Life$	−0.452**	−0.332	−0.442**	−0.459**
	$p = 0.016$	$p = 0.107$	$p = 0.027$	$p = 0.020$
$Total\ Assets$	0.341***	0.349***	0.490***	0.513***
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$Leverage : D/A$	0.004	−0.004	−0.049	−0.035
	$p = 0.930$	$p = 0.927$	$p = 0.338$	$p = 0.515$
$Non - CoreAct.$	0.025**	0.015	−0.005	−0.004
	$p = 0.021$	$p = 0.299$	$p = 0.592$	$p = 0.756$
RoI	0.003	−0.0005	0.008	0.009
	$p = 0.872$	$p = 0.982$	$p = 0.714$	$p = 0.676$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	941	941	941	941
R^2	0.834	0.801	0.823	0.807
Adjusted R^2	0.830	0.796	0.818	0.802
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: OLS Panel Regression: Leverage as D/A Ratio

The table shows the results of the OLS panel regression as in Table 4, but leverage is defined as the debt to asset ratio. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ (FIN) and (NoFIN) refers to the CoVaR measure on historical quantiles w.r.t. the global financial and non-financial system. ΔCoVaR$_{EG}$ (FIN) and (NoFIN) refers to the same systems, but use the estimation technique by Ergün and Girardi (2013). Regression parameters are standardized with mean 0 and standard deviation 1.

	Dependent variable:			
	ΔCoVaR$_{hist}$ (FIN)	ΔCoVaR$_{hist}$ (NoFIN)	ΔCoVaR$_{EG}$ (FIN)	ΔCoVaR$_{EG}$ (NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	0.472***	0.372**	0.477***	0.500***
	$p = 0.004$	$p = 0.043$	$p = 0.010$	$p = 0.006$
$Life$	−0.523***	−0.413**	−0.489**	−0.512***
	$p = 0.004$	$p = 0.039$	$p = 0.013$	$p = 0.008$
Total Assets	0.347***	0.356***	0.489***	0.515***
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
Leverage	0.045	0.049	0.026	0.024
	$p = 0.211$	$p = 0.172$	$p = 0.395$	$p = 0.461$
$Non-Core$ *Act.*	0.065	0.046	0.006	0.036
	$p = 0.207$	$p = 0.463$	$p = 0.827$	$p = 0.346$
RoI	0.024	0.018	0.035	0.043
	$p = 0.329$	$p = 0.506$	$p = 0.207$	$p = 0.103$
NCR	−0.051***	−0.051*	−0.069***	−0.090***
	$p = 0.004$	$p = 0.065$	$p = 0.001$	$p = 0.001$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	926	926	926	926
R^2	0.836	0.803	0.823	0.811
Adjusted R^2	0.832	0.798	0.818	0.806
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 22: OLS Panel Regression: Net Claims Ratio (NCR)

The table shows the results of the OLS panel regression as in Table 4, and includes the Net Claims Ratio, defined as the ratio of total net claims and benefits to total net premiums earned (SNL Key: 245623). All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ (FIN) and (NoFIN) refers to the CoVaR measure on historical quantiles w.r.t. the global financial and non-financial system. ΔCoVaR$_{EG}$ (FIN) and (NoFIN) refers to the same systems, but use the estimation technique by Ergün and Girardi (2013). Regression parameters are standardized with mean 0 and standard deviation 1.

	Dependent variable:			
	ΔCoVaR$_{hist}$ (FIN)	ΔCoVaR$_{hist}$ (NoFIN)	ΔCoVaR$_{EG}$ (FIN)	ΔCoVaR$_{EG}$ (NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	0.435***	0.324*	0.431**	0.440**
	$p = 0.007$	$p = 0.076$	$p = 0.023$	$p = 0.019$
$Life$	−0.516***	−0.396**	−0.481**	−0.499**
	$p = 0.005$	$p = 0.050$	$p = 0.018$	$p = 0.014$
$Total\ Liabilities$	0.344***	0.349***	0.484***	0.509***
	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$
$Leverage$	0.041	0.046	0.018	0.019
	$p = 0.230$	$p = 0.172$	$p = 0.542$	$p = 0.563$
$Non-Core\ Act.$	0.029**	0.020	−0.002	−0.001
	$p = 0.017$	$p = 0.199$	$p = 0.870$	$p = 0.950$
RoI	0.007	0.004	0.011	0.012
	$p = 0.728$	$p = 0.867$	$p = 0.637$	$p = 0.587$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	941	941	941	941
R^2	0.835	0.801	0.818	0.802
Adjusted R^2	0.831	0.796	0.813	0.798
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 23: OLS Panel Regression: Size as natural log of Total Liabilities

The table shows the results of the OLS panel regression as in Table 4, but size is defined as the natural logarithm of insurer's total liabilities. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ (FIN) and (NoFIN) refers to the CoVaR measure on historical quantiles w.r.t. the global financial and non-financial system. ΔCoVaR$_{EG}$ (FIN) and (NoFIN) refers to the same systems, but use the estimation technique by Ergün and Girardi (2013). Regression parameters are standardized with mean 0 and standard deviation 1.

	Dependent variable:			
	ΔCoVaR$_{hist}$ (H:FIN)	ΔCoVaR$_{hist}$ (S:FIN)	ΔCoVaR$_{hist}$ (H:NoFIN)	ΔCoVaR$_{hist}$ (S:NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	1.239***	0.951**	1.205**	0.749*
	$p = 0.009$	$p = 0.035$	$p = 0.020$	$p = 0.064$
$Life$	−1.405***	−1.316**	−1.444***	−0.974**
	$p = 0.006$	$p = 0.013$	$p = 0.009$	$p = 0.049$
$Total\ Assets$	0.307***	0.416***	0.456***	0.302**
	$p = 0.00000$	$p = 0.003$	$p = 0.00000$	$p = 0.021$
$Leverage:\ D/E$	0.022	0.222*	−0.036	0.190
	$p = 0.696$	$p = 0.074$	$p = 0.650$	$p = 0.108$
$Non-Core\ Act.$	−0.214	0.227**	−0.357**	0.251***
	$p = 0.171$	$p = 0.012$	$p = 0.021$	$p = 0.007$
RoI	−0.084	0.100	−0.079	0.077
	$p = 0.202$	$p = 0.366$	$p = 0.300$	$p = 0.474$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	95	95	95	95
R^2	0.911	0.805	0.862	0.811
Adjusted R^2	0.888	0.742	0.827	0.749
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 24: OLS Baseline Regression for the 10% highest and smallest Debt/Equity Ratios as Leverage for Measure 1

The table shows the results of the OLS panel regression as in Table 4, but with leverage as debt/equity ratio. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ (FIN) and (NoFIN) refers to the CoVaR measure on historical quantiles w.r.t. the global financial and non-financial system, and for samples with the highest (H) and smallest (S) debt to equity ratio. Regression parameters are standardized with mean 0 and standard deviation 1.

	Dependent variable:			
	ΔCoVaR$_{EG}$ (H:FIN)	ΔCoVaR$_{EG}$ (S:FIN)	ΔCoVaR$_{EG}$ (H:NoFIN)	ΔCoVaR$_{EG}$ (S:NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	1.168*	1.104***	1.251**	0.926***
	$p = 0.057$	$p = 0.009$	$p = 0.038$	$p = 0.010$
$Life$	-1.255^{*}	-1.225^{**}	-1.415^{**}	-1.036^{***}
	$p = 0.057$	$p = 0.013$	$p = 0.030$	$p = 0.008$
$Total\ Assets$	0.543***	0.489***	0.575***	0.507***
	$p = 0.000$	$p = 0.0001$	$p = 0.000$	$p = 0.00001$
$Leverage:\ D/E$	0.055	0.053	0.073	0.022
	$p = 0.362$	$p = 0.524$	$p = 0.226$	$p = 0.781$
$Non-Core\ Act.$	-0.186	0.006	-0.204	0.020
	$p = 0.295$	$p = 0.926$	$p = 0.263$	$p = 0.764$
RoI	-0.141	0.020	-0.122	0.022
	$p = 0.176$	$p = 0.828$	$p = 0.196$	$p = 0.810$
Year Fixed Effects	Y	Y	Y	Y
Geo Fixed Effects	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	95	95	95	95
R^2	0.858	0.818	0.853	0.827
Adjusted R^2	0.822	0.759	0.816	0.771
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 25: OLS Baseline Regression for the 10% highest and smallest Debt/Equity Ratios as Leverage for Measure 2

The table shows the results of the OLS panel regression as in Table 4, but with leverage as debt/equity ratio. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{EG}$ (FIN) and (NoFIN) refers to the CoVaR measure by Ergün and Girardi (2013) w.r.t. the global financial and non-financial system, and for samples with the highest (H) and smallest (S) debt to equity ratio. Regression parameters are standardized with mean 0 and standard deviation 1.

	Dependent variable:			
	ΔCoVaR$_{hist}$ (FIN)	ΔCoVaR$_{hist}$ (NoFIN)	ΔCoVaR$_{EG}$ (FIN)	ΔCoVaR$_{EG}$ (NoFIN)
	(1)	(2)	(3)	(4)
$Life^2$	0.137	0.074	0.194*	0.129
	$p = 0.348$	$p = 0.665$	$p = 0.077$	$p = 0.153$
$Life$	-0.217	-0.139	-0.220^{*}	-0.165^{*}
	$p = 0.173$	$p = 0.456$	$p = 0.058$	$p = 0.072$
$Total\ Assets$	0.109*	0.093	0.124***	0.105***
	$p = 0.064$	$p = 0.183$	$p = 0.0005$	$p = 0.001$
$Leverage$	0.038	0.027	0.004	0.015
	$p = 0.347$	$p = 0.490$	$p = 0.874$	$p = 0.542$
$Non-Core\ Act.$	0.723	1.213	-0.693	-0.014
	$p = 0.594$	$p = 0.440$	$p = 0.533$	$p = 0.991$
RoI	-0.019	-0.031	-0.045	-0.040
	$p = 0.571$	$p = 0.362$	$p = 0.163$	$p = 0.122$
$Insurer-Correlation$	0.338***	0.357***	0.526***	0.583***
	$p = 0.000$	$p = 0.00001$	$p = 0.000$	$p = 0.000$
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Geo Fixed Effects	*Y*	*Y*	*Y*	*Y*
Clustered SE	*Y*	*Y*	*Y*	*Y*
Observations	618	618	618	618
R^2	0.885	0.864	0.901	0.913
Adjusted R^2	0.880	0.859	0.897	0.909
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 26: OLS Baseline Regression with Insurer-Correlation

The table shows the results of the OLS panel regression as in Table 4. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. ΔCoVaR$_{hist}$ (FIN) and (NoFIN) refers to the CoVaR measure on historical quantiles w.r.t. the global financial and non-financial system. ΔCoVaR$_{EG}$ (FIN) and (NoFIN) refers to the same systems, but use the estimation technique by Ergün and Girardi (2013). Regression parameters are standardized with mean 0 and standard deviation 1. Leverage is defined as the debt to equity ratio. Insurer-Correlation is the insurer's yearly contemporaneous correlation coefficient with the global insurance system as defined by Regele (2020). The system consists of 386 international insurers, daily equity data was collected from SNL Financial (S&P Market Intelligence) and Datastream. The Pearson correlation is calculated between an insurer's stock return in a given year and the market-capitalization weighted return of the insurance system that excludes the insurer under consideration.

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