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Insurance Business Diversification and Systemic Risk*

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Abstract

Risk diversification, for example in terms of business lines with imperfectly correlated cash flows, can reduce the financial distress risk of an institution due to coinsurance effects. Therefore, business diversification might also lower systemic risk from a "domino" perspective, in which the financial distress of an institution causes financial contagion risks to other institutions that result in systemic risk. The underwriting of risks is typically considered as not systemically risky by itself and life and non-life insurance shows substantially different underwriting characteristics. Therefore, this paper studies if insurance business diversification between life and non-life insurance can create a financially stabilizing diversification effect reducing systemic risk. By means of theoretical and empirical approaches, the findings suggest that diversified insurers engaging in both insurance lines have, on average, a lower contribution to systemic risk than monoline life and non-life insurers. More specifically, insurers with a business allocation in the range of 54% life insurance show, on average, the lowest contribution to systemic risk. These findings have important implications for the design of macroprudential insurance regulation, which currently neglects the financially stabilizing potential of insurance business diversification.

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 spillover of losses from a financially distressed insurer to other institutions through financial contagion, causing negative consequences for the real 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 insurance regulation developed the concept of systemically important insurers in the aftermath of the global financial crisis. The main aim of this regulatory approach is to identify systemically relevant insurers, whose financial distress could result in systemic risk, and to reduce the financial contagion risks associated with these specific 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) (2016)). Although the identification of systemically relevant insurers through the indicator-based approach proposed by the International Association of Insurance Supervisors (IAIS) has been controversially discussed (e.g. Chow et al. (2018)), there is substantial evidence in the literature underlining that insurers can contribute to systemic risk (e.g. Kaserer and Klein (2019), Bierth et al. (2015), Weiß and Mühlnickel (2014), Billio et al. (2012)).[1]

Risk diversification, for example with regard to business activities, typically reduces an individual institution's distress risk through cash flow smoothing and coinsurance effects (e.g. Köhler (2015), Stiroh (2006)). Thus, business diversification might also lower systemic risk from the ”domino” perspective, as the financially stabilizing diversification effect should reduce financial contagion risks. For example, if a financial institution gets hit by a shock, potential coinsurance effects between the business lines should reduce the institution's financial distress risk and thus,

[1] The ”individual insurer monitoring” of the IAIS aims to assess systemic risk in terms of financial contagion risks stemming from an insurer's financial 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) (2016)).

reduce the potential for a spillover of losses to other institutions resulting in systemic risk. For insurers, life and non-life insurance shows substantially different underwriting characteristics that might generate a coinsurance effect between both business lines that could reduce systemic risk. Moreover, findings by Cummins and Weiss (2014) and Harrington (2009) suggest that the insurance business in terms of underwriting risks does not contribute to systemic risk by itself. Thus, diversifying across insurance lines should rather reduce systemic risk than increase it. However, the insurance literature provides no clear evidence on the existence of a financially stabilizing diversification effect between life and non-life insurance and how it is linked to systemic risk. Therefore, this paper studies if a diversification potential between life and non-life insurance exists and to what extent it affects the insurer's contribution to systemic risk in terms of financial contagion.

It is important to study the link between insurance business diversification and systemic risk, since current macroprudential insurance regulation does not take it into account so far. For example, the IAIS evaluates the systemic relevance of individual insurers through an indicator-based model in the "individual insurer monitoring" exercise, which particularly focuses on insurer characteristics like size, but does not consider a potentially risk reducing effect of insurance business diversification on systemic risk (International Association of Insurance Supervisors (IAIS) (2019b), International Association of Insurance Supervisors (IAIS) (2018)). Given the controversial debates on the indicator-based identification approach, with the exclusion of MetLife from the list of systemically important insurers by court decision in 2016 as an example (United States District Court for the District of Columbia (2016)), findings on the influence of insurance business diversification on systemic risk could help to develop macroprudential insurance regulation further. For example, given the substantial regulatory costs associated with an insurer's contribution to systemic risk (Naubert and Tesar (2019)), supplementing the indicator-based approach by taking into account a potentially risk reducing diversification effect could reduce regulatory costs. It would also support supervisors in allocating monitoring efforts to the insurers most threatening financial stability.

Therefore, Section 2.1 studies differences in the underwriting characteristics between life and non-life insurance and potential implications on a financially stabilizing diversification effect. Quantitative evidence on cash flows related to both insurance lines suggests the existence of a diversification effect. Cash flows related to life insurance are less volatile and mainly uncorrelated with cash flows related to non-life insurance. A theoretical portfolio model demonstrates in Section 2.2

how business diversification between life and non-life insurance could influence systemic risk. The model focuses on counterparty risk as an important channel for financial contagion resulting in systemic risk (e.g. International Association of Insurance Supervisors (IAIS) (2019b)).[2] Due to the imperfectly correlated cash flows from life and non-life insurance, the model predicts a u-shaped relation between systemic risk and the business allocation between both insurance lines. More specifically, the model suggests the existence of a systemic risk minimizing insurance business allocation with an overweight towards the less volatile life insurance business. Therefore, Section 3 provides the empirical model to test the theoretical hypotheses on the influence of insurance business diversification on systemic risk in terms of financial contagion. The insurer's contribution to systemic risk is estimated by the ΔCoVaR, which is a frequently used empirical measure originally proposed by Adrian and Brunnermeier (2016). In contrast to an indicator-based measurement of insurer's contribution to systemic risk with accounting data, the ΔCoVaR uses the insurer's stock returns as input, thereby reflecting the market's perspective on systemic risk in a forward-looking manner. The systemic consequences of an insurer's distress are estimated on the global banking, insurance and non-financial sector. The panel regression on a sample of 68 international insurers from 2000 to 2020 in Section 4 supports the existence of a u-shaped relation between insurance business diversification in terms of life and non-life insurance and systemic risk. In line with the theoretical hypotheses, undiversified monoline insurers conducting only life or non-life insurance show, on average, the highest level of systemic risk in terms of financial contagion. In particular, the results show that systemic risk, on average, can be minimized through a business allocation in the range of 54% life insurance and 46% non-life insurance. Section 4.3 then discusses potential policy implications of the findings. Monoline life and monoline non-life insurers should be monitored more closely than diversified insurers, as undiversified insurers are associated with higher financial contagion risks if they get hit by a shock. Since macroprudential insurance regulation does not take the extent of insurance business diversification between life and non-life insurance into account, supervisors could, for example, use the insurer's business allocation as a further indicator for assessing the systemic relevance of insurers.

This paper is based on a broad stream of literature. It generally adds further insights to

[2]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)).

the insurance diversification literature. Previous research, for instance Shim (2017b), Che and Liebenberg (2017), Berry-Stölzle et al. (2012), Elango et al. (2008) and Liebenberg and Sommer (2008) focus on the effects of product diversification within the non-life insurance business on the insurer's financial performance. However, evidence regarding the influence of insurance business diversification in terms of life and non-life insurance on financial stability at the individual insurer- and macroeconomic-level is largely missing. Therefore, this paper provides important findings underlining the existence of a financially stabilizing diversification potential between life and non-life insurance. The paper also contributes to the systemic risk literature, in particular, with a focus on insurer's characteristics that contribute to systemic risk. 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 several insurer-related characteristics and activities on systemic risk. These studies categorize insurers into life or non-life insurers, but neglect potential diversification effects between both insurance lines with regard to systemic risk. In contrast, Kaserer and Klein (2019) explicitly categorize multiline insurers in the insurer sample, but do not study the influence of differences in the insurers' business allocation on systemic risk. Therefore, this paper uses a continuous measure of the insurer's business allocation and studies the marginal influence of insurance business diversification on systemic risk. The findings of this paper provide important suggestions to further improve current macroprudential insurance regulation. Moreover, the findings of the paper also contribute to a further alignment of micro- and macroprudential regulatory aims. While microprudential insurance regulation focuses on reducing the individual insurer's distress risk, it does not consider potential implications on a macroeconomic level (European Insurance and Occupational Pensions Authority (EIOPA) (2017)). Hence, providing evidence on how insurance business diversification at the microprudential insurer-level also affects systemic risk at the macroprudential level helps to further synchronize micro- and macroprudential insurance regulation.

The rest of the paper is structured as follows. Section 2 studies the diversification potential between life and non-life insurance and its potential influence on the insurer's contribution to systemic risk in terms of financial contagion. Section 3 outlines the empirical model and Section 4 presents the results, followed by a discussion of policy implications in Section 4.3. Section 5 concludes.

2 Impact of Business Diversification on Systemic Risk

The case of AIG during the global financial crisis from 2007-09 has shown that the financial distress of an individual insurer can cause systemic risk. The huge losses that AIG has incurred, mainly resulting from its non-insurance activities in terms of CDS trading and security lending transactions (McDonald and Paulson (2015)), caused substantial contagion risks to other institutions in the financial system. In that regard, three particular channels were mainly responsible for the systemic relevance of AIG during the crisis (Financial Stability Oversight Council (FSOC) (2013b)): i) counterparty risks of other financial institutions to AIG, ii) potential loss spirals in asset prices due to fire sales of AIG's assets and iii) a lack of substitutability for policyholders in the commercial insurance market, in which AIG was a market player. In order to limit systemic risk stemming from an individual insurer's distress, macroprudential insurance regulation builds on the concept of systemically important insurers, aiming to reduce the distress risk of individual insurers and thereby lowering potential contagion risks (e.g. European Insurance and Occupational Pensions Authority (EIOPA) (2019), International Association of Insurance Supervisors (IAIS) (2019b), International Monetary Fund (IMF) (2016)).

Eling and Jia (2018) find the level of insurer's business volatility to be a determinant for the insurer's financial distress risk. Since the underwriting of risks is typically not systemically risky by itself (Cummins and Weiss (2014), Harrington (2009)), and given that underwriting risks of life and non-life insurance business differ substantially from each other, a combination of both insurance lines might create a financially stabilizing diversification effect. From a classic portfolio perspective, the diversification effect should reduce the volatility of a diversified insurer's equity cash flow and hence, reduce the insurer's financial distress risk, resulting in lower systemic risk in terms of financial contagion. However, insurance business diversification has not been taken into account so far by macroprudential insurance regulation (International Association of Insurance Supervisors (IAIS) (2019a), International Association of Insurance Supervisors (IAIS) (2016)). Evidence on the potential diversification effect between life and non-life insurance is largely missing in the literature, since most studies in context of insurance business diversification focus on product diversification in the non-life insurance segment (e.g. Shim (2017b), Che and Liebenberg (2017), Berry-Stölzle et al. (2012), Elango et al. (2008), Liebenberg and Sommer (2008)). Therefore, the subsequent sections study whether a combination of life and non-life insurance business could potentially create a financially stabilizing diversification effect for insurers.

2.1 Cash Flow Characteristics of Insurance Activities

Life insurance is typically considered as a 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 are uncertain ex ante to a loss event. But even ex post to a loss event, non-life insurers can have substantial payout tails due to the uncertainty in the exact amount of indemnity payments to settle the claims incurred (Cummins and Weiss (2016)). Thus, payout tails can further raise the volatility of non-life underwriting cash flows compared to life insurance. Moreover, the premium income from short-term non-life insurance products typically fluctuates more over time compared to life insurance products. The average duration of a life insurance contract with a typically fixed premium level is more than 10 years, whereas it is usually one year for non-life insurance contracts (Bank of England (BoE) (2015b), European Insurance and Occupational Pensions Authority (EIOPA) (2014a)). The short-term pricing principle in non-life insurance allows insurers to adjust their premiums frequently, for instance, in reaction to market developments or changes in the underwriting risk exposure.

These distinctive differences between life and non-life insurance suggest that cash flows from non-life insurance business 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 generating financially stabilizing coinsurance effects could emerge. For example, by means of profit and loss transfer agreements, a holding company consisting of a life and a non-life insurance subsidiary can hedge losses from one insurance line with profits from the other insurance line. As 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 the distinctive underwriting differences between both insurance lines (e.g. Getmansky et al. (2018), Bank of England (BoE) (2014), Financial Stability Oversight Council (FSOC) (2013a)).

Table 1 motivates the potential for a financially stabilizing diversification effect between life and non-life insurance based on insurance-related cash flows from a sample of 56 pure monoline life and non-life insurers from 2005 to 2019. The cash flow analysis shows that life insurers have, on average, substantially lower volatility levels in their premium and claim cash flows (0.12/0.27) than non-life insurers (0.23/0.58). Since the average correlation between life and non-life insurers with regard to premium income (0.02) and claim payments (0.03) is close to zero, combining both insurance lines could lead to a financially stabilizing diversification potential that lowers the diversified insurer's distress risk compared to an undiversified monoline life or non-life insurer.

	Life St. Dev.	Non-Life St. Dev.	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 standard deviation (St. Dev.) of the annual growth rates with regard to cash flows in terms of premium income and underwriting claims and benefit payments. Correlation shows the average Pearson correlation coefficients between the growth rates of the life and non-life insurance-related cash flows. 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 benefit payments are 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 in US-$ from SNL Financial (S&P Market Intelligence). Details on the sample and data is given in Appendix A.1.

However, studying the diversification potential of life and non-life insurance at the individual insurer level is not informative about the influence of business diversification on the tail dependence between financial institutions and hence, how economic shocks can propagate through the system by means of financial contagion. Therefore, the subsequent part derives an economic intuition on the potential influence of insurance business diversification on systemic risk in terms of financial contagion. The analysis is based on an exemplary theoretical portfolio model, and derives testable implications for empirical validation.

2.2 Theoretical Portfolio Model

The theoretical portfolio model illustrates how insurance business diversification can influence systemic risk in terms of financial contagion from a distressed insurer to other institutions. The model approximates systemic risk by means of counterparty credit risk, which is an important transmission channel for shocks to create systemic risk (International Association of Insurance Supervisors (IAIS) (2019b), Financial Stability Oversight Council (FSOC) (2013b)). The model's underlying rationale is the insurer has financial linkages to other institutions, for example due to derivatives trading or security lending activities, and can become financially distressed in case of a shock, which leads to a loss propagation to the insurer's counterparties if the insurer fails to repay its financial obligations.[3] 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)).

The model is based on a portfolio perspective of an insurance holding that has the opportunity to invest in one life and one non-life insurance company. This set-up is similar to the one 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 on the financial performance of banks. At time $t = 0$, the insurance holding invests the fraction $\alpha \in [0, 1]$ in the life (L) and the residual amount $1 - \alpha$ 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.[4] 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 in 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

$$EL = D - E[\min(D, R)] = (D - \mu_R)\,\Phi(\frac{D - \mu_R}{\sigma_R}) + \sigma_R\,\Phi'(\frac{D - \mu_R}{\sigma_R}) \tag{1}$$

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 $t = 1$.

[3]In Q1 2017, the sum of security repurchase agreements, loans and security lending liabilities comprised 2.3% (0.7%) of US life (non-life) total liabilities (Board of the Governors of the Federal Reserve System (2017)).

[4]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.

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 R 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.[5] Hence, the expected loss for the counterparty is influenced by the volatility of the holding's total equity cash flow, which is given by

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

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} 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

$$\begin{aligned}\frac{\partial EL}{\partial \alpha} &= (D - \mu_R)\,\frac{\partial \Phi(z)}{\partial \alpha} + \frac{\partial \sigma_R}{\partial \alpha}\,\Phi'(z) + \sigma_R\,\frac{\partial \Phi'(z)}{\partial \alpha} \\ &= \frac{1}{2\sigma_R}\,\Phi'(z)\,\frac{\partial \sigma_R^2}{\partial \alpha}\end{aligned} \tag{3}$$

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

$$\alpha^* = \frac{\sigma_{NL}^2 - \sigma_L\,\sigma_{NL}\,\rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\,\sigma_L\,\sigma_{NL}\,\rho} \tag{4}$$

A detailed derivation is provided in Appendix A.2. Based on the model, business diversification between life and non-life insurance can reduce financial contagion in terms of counterparty credit risk if the correlation ρ between the equity cash flows from both insurance business lines is sufficiently small. As Section 2.1 suggests almost uncorrelated cash flows between life and non-life insurance, a diversifying multiline insurance company should reduce systemic risk in terms of financial contagion compared to an undiversified life or non-life monoline insurer (Hypothesis I). Hence, the relationship between systemic risk and the insurance business allocation between life and non-life insurance (α)

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

should be captured by a u-shaped relation. As Section 2.1 suggests that life insurance is less volatile than non-life insurance, the optimal life insurance business allocation α^* minimizing systemic risk in terms of financial contagion should be higher than 50% (Hypothesis II).

3 Data

In order to test the theoretical hypotheses from the portfolio model on the influence of business diversification between life and non-life insurance, the following section outlines the construction of the insurer sample and defines the empirical model.

3.1 Sample Construction

Publicly listed insurers from all geographic regions in SNL Financial (S&P Market Intelligence) are selected over the time period of 2000 to 2020. In order to mitigate selection bias, insurers that are listed as out of business or acquired are included in the sample. Then, all insurers without an ISIN number, with missing data on the premium income and very small insurers with total assets smaller than 60 million US-$ are omitted from the sample. The insurer's stock price is collected as the daily close price and all data for the sample is collected in US-$ in order to mitigate a currency bias. In order to ensure sufficient liquidity in the data, insurers with less than 5 years of data and firm-year observations with less than 200 daily returns per year are omitted from the sample. Moreover, due to a potential bias from OTC deals, insurers with a daily stock return of more than 80% or less than -80% and firm-year observations in which more than 25% of daily returns are zeroes are omitted. The data cleaning results in a sample of 159 international insurers that represent the global insurance system for the analysis (Table 13).

The business model of insurers is typically very stable and pure monoline life and non-life insurers usually do not change their business model over time. As the insurance business allocation of monoline insurers does not provide any variation in the data that can be used to study the marginal impact of business diversification between life and non-life insurance on systemic risk, the final sample for the baseline regression analysis consists of multiline insurers engaging in both insurance lines and economic monoline insurers that allocate 99% of their premium income to either life or non-life insurance. Robustness checks are also conducted on an insurer sample including monoline insurers with 100% premium income from either life or non-life insurance. The final sample for the regression analysis consists of 68 insurers with observations from 2000 to 2020 and most insurers are located in Europe (40%), followed by North America (27%) and Asia-Pacific (19%). The list of insurers is given in Table 9 in Appendix A.3.

3.2 Systemic Risk Measure

Since the analysis is focusing on systemic risk in terms of financial contagion from a distressed insurer to other institutions in an economic system, the ΔCoVaR as empirical systemic risk measure is used. The measure has been originally proposed by Adrian and Brunnermeier (2016) and has been used frequently under different estimation approaches in the systemic risk literature (e.g. Brunnermeier et al. (2020), Bierth et al. (2015), Weiß and Mühlnickel (2014), Mainik and Schaanning (2014), Ergün and Girardi (2013)).[6] 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, i.e. the system's Value-at-Risk conditional on institution i being in distress, and the system's tail risk if the institution is in its median state. Thus, the measure captures the potential that a financially distressed insurer contributes additional losses to other institutions in a given system, and is defined as

$$\Delta\text{CoVaR}_q^{S|i} = \text{CoVaR}_{r^i=VaR^i(q)}^{S|i} - \text{CoVaR}_{r^i=VaR^i(0.5)}^{S|i} \tag{5}$$

where q denotes the quantile level of equity returns for a given system S and insurer i. In line with the literature, the 5% quantile of stock returns is used to indicate financial distress, corresponding to the insurer's 5% worst returns (e.g. Bierth et al. (2015)).

The conditional ΔCoVaR captures the time-varying dependence between the tail risks of the institution and the system under consideration and is estimated based on a set of state variables as given in Appendix A.4. For the estimation, three different systems are employed. First, and similar to Bierth et al. (2015), the global banking system (BAN) represented by the MSCI World

[6]The ΔCoVaR 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 issued by 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.

Banking Index is used in order to study the potential spillover of losses from insurers to banks. Second, the global insurance system (INS) represented by a self-constructed index of 159 insurers is employed. For each insurer-specific ΔCoVaR estimation, an own insurance index consisting of the residual 158 insurers in the system is constructed, because a contemporaneous inclusion of the insurer under consideration in the index would otherwise bias the ΔCoVaR estimation by a constructed correlation. Third, 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)), a global non-financial system (NoFin) is employed in order to study the direct impact of an insurer's distress on the real economy. The non-financial system is represented by Datastream's World Non-Financial Index, which covers firms from different industrial sectors, e.g. food, pharmaceuticals or software, and different geographical regions. A detailed description of the systems employed is given in Appendix A.4. The estimation of the ΔCoVaR is based on daily return data, which is collapsed into weekly frequency for the quantile regressions. For the panel regression with yearly balance sheet and income statement data, the annual mean value of the weekly estimates is then taken to represent the average systemic risk contribution of an insurer in a given year. Estimates of the ΔCoVaR are reported in negative values, such that a higher value relates to a higher systemic risk contribution.

3.3 Explanatory Variables

The main variable of interest is the insurer's business diversification between life and non-life insurance. The ratio of net premiums earned in life and health insurance relative total net premiums earned (including life and non-life insurance) is used to capture the influence of insurance business diversification on systemic risk.[7] Net premiums earned capture the underwriting risk taken by the insurer and, since these premiums are net of reinsurance, the ratio mitigates a potential reinsurance bias in the results. The ratio is a continuous measure of the insurer's business diversification extent, indicating 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

[7] 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)).

on systemic risk, in contrast to frequently used binary measures that categorize insurers only into diversified or undiversified insurers (e.g. Liebenberg and Sommer (2008)). The regression model uses a quadratic term on the life ratio in order to capture a potentially u-shaped relation between insurance business diversification in terms of life and non-life insurance and systemic risk in terms of financial contagion.

The regression model controls for several insurer characteristics that could influence systemic risk. The insurer's size is approximated by the natural logarithm of the insurer's total assets. For instance, Weiß and Mühlnickel (2014) find insurer's size to be significantly related to the insurer's systemic risk contribution and it is also an important determinant in the indicator-based model to identify systemically relevant insurers (International Association of Insurance Supervisors (IAIS) (2019b), International Association of Insurance Supervisors (IAIS) (2018)). The rationale is that large insurers are more likely to be "too-big-to-fail" as well as "too-complex-to-fail" than small insurers, and hence, potentially engage in riskier activities and propagate shocks more easily to other institutions (International Association of Insurance Supervisors (IAIS) (2016)). Moreover, large insurers are more likely to hold and sell similar assets, potentially causing adverse fire sale effects to other large institutions, which increases systemic risk (e.g. Getmansky et al. (2018), Ellul et al. (2018), Ellul et al. (2011)). Hence, the insurer's size is expected to increase the insurer's systemic risk contribution in terms of financial contagion.

The global financial crisis of 2007-09 has shown that duration mismatches between assets and liabilities can contribute to systemic risk in terms of financial contagion (Brunnermeier et al. (2009), Brunnermeier (2009)). Banks usually finance their assets by means of debt obligations under potentially substantial duration mismatches. However, since insurers typically finance their assets by "equity-like" insurance premiums paid upfront by policyholders and follow duration matching principles between assets and liabilities, leverage should be measured differently for insurers compared to banks (Thimann (2014), Kessler (2013)). Therefore, the baseline regression model follows Shim (2017a) by defining leverage in terms of the ratio of net premiums earned to policyholder surplus and refrains from using a more bank-oriented definition, for instance by means of a debt to equity ratio. Since Chen and Wong (2004) and Carson and Hoyt (1995) show that higher leverage ratios can increase the insurer's distress risk, a higher leverage ratio should increase systemic risk.

Insurers also engage in non-insurance related activities that can influence contagion risks, for instance derivatives trading or security lending activities as in the case of AIG (McDonald and Paulson (2015)). The model controls for an insurer's non-core activities in line with Bierth et al. (2015) by using the ratio of total liabilities over insurance reserves. A higher ratio for non-core activities should increase the insurer's externalities in the system and hence, increase systemic risk in terms of financial contagion. In order to capture differences in the underwriting portfolios of insurers, for example in terms of insurance products, which could influence the insurer's financial distress risk, the model includes the net-claims-ratio defined as the ratio of total net claims and benefits to total net premiums earned. It is expected that a higher net-claims-ratio increases the insurer's distress risk due to higher underwriting losses and thereby increases the insurer's contribution to systemic risk. The insurer's operating profitability can also influence financial contagion risks (e.g. Bierth et al. (2015) and Weiß and Mühlnickel (2014)). As insurers are typically conservative investors, a higher return on their investments could increase the profitability and resilience against shocks. Thus, a higher return on investments might lower the insurer's contribution to systemic risk due to lower distress risk. However, higher investment returns might also be associated with higher investment risks, which could increase the insurer's contribution to systemic risk in case of a shock. The model employs the insurer's return on investments (RoI) defined as the ratio of absolute investment income to total assets and expects the influence on systemic risk to be unrestricted. In order to capture the general influence of the insurer's profitability on systemic risk, the model uses the insurer's return on equity (RoE) and expects the influence to be unrestricted.

3.4 Regression Model

The multivariate panel regression is specified as follows

$$Y_{i,t} = \beta_0 + \beta_1\, Life^2_{i,t-1} + \beta_2\, Life_{i,t-1} + \beta_Z\, Z_{i,t-1} + \epsilon_{i,t} \tag{6}$$

where $Y_{i,t}$ stands for the ΔCoVaR estimate as systemic risk measure of institution i in year t, $Life_{i,t}$ denotes the ratio of life insurance business to total insurance business, $Z_{i,t}$ captures the control variables and $\epsilon_{i,t}$ denotes the error term. Table 8 in Appendix A.3 gives an overview of all variables used for the panel regression analysis.

Macro-economic trends, for example the transition to the low interest rate environment on the capital markets, and regional trends, such as changing insurance demands or changes in the regulatory environment, are captured in the model by including year and geographic fixed effects. The model also uses clustered standard errors at the insurer-level, in order to account for serial correlation within the insurer-related data. Since the business allocation of insurers is relatively persistent over time, using insurer-fixed effects would absorb most of the variation in the data. Therefore, the model follows van Oordt and Zhou (2018), Chow et al. (2018) and Liebenberg and Sommer (2008) by refraining from using insurer-fixed effects. In order to mitigate reverse causality inducing endogeneity, for instance that insurers adjust their business allocations to their contemporaneous contribution to systemic risk, the model follows 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 insurance ratio, the model might suffer from structural multicollinearity. Hence, the regression parameters are standardized with mean 0 and standard deviation 1 (e.g. López-Espinosa et al. (2009)). The standardization also increases comparability between the marginal effects of the independent variables across the different systems employed in the ΔCoVaR estimation.

3.5 Descriptive Statistics

In line with the literature, the statistics show that the financial distress of insurers can contribute to systemic risk by causing additional losses to other institutions (e.g. Bierth et al. (2015), Weiß and Mühlnickel (2014)). The financial distress of the average insurer in the sample increases the tail risk in the global banking sector (BAN) due to financial contagion by 0.4%, in the global insurance sector (INS) by 0.5% and in the global non-financial sector (NoFin) by 0.3% per day. In particular, the spillover of losses from insurers is highest to other insurers, followed by banks and the real economy approximated by the NoFin sector. In contrast to previous studies that focus only on the spillover of losses from insurers to other financial institutions, the explicit inclusion of the non-financial sector in the sample highlights the direct transmission channel of shocks from insurers to the real economy. The average insurer allocates a fraction of 42% of its insurance business to life insurance, which constitutes an overweight to non-life insurance. The sample also includes economic monoline insurers with 99% life and non-life insurance business. The size of the average insurer in the sample is 118 billion US-$ in total assets, which is larger than in Bierth et al. (2015) and Weiß and Mühlnickel (2014), but the sample also includes very small insurers (78 million US-$).

Statistic	Mean	St. Dev.	Min	Max
Systemic Risk Measures				
ΔCoVaR_{BAN}	0.004	0.002	-0.002	0.022
ΔCoVaR_{INS}	0.005	0.003	-0.002	0.024
$\Delta\text{CoVaR}_{NoFin}$	0.003	0.002	-0.001	0.012
Insurer Characteristics				
Life Insurance Ratio	0.42	0.29	0.01	0.99
Net Claims Ratio	0.84	0.28	0.18	3.41
Non-Core Activities	1.78	1.90	1.02	24.02
Leverage	1.34	1.16	0.03	21.94
Debt to Asset Ratio	0.07	0.12	0.0	0.71
Total Assets (bn US-$)	117.8	208.3	0.078	1,181.0
Total Liabilities (bn US-$)	107.1	194.1	0.031	1,058.5
RoI	0.03	0.02	-0.07	0.14
RoE	0.09	0.09	-0.85	0.60

Table 2: Descriptive Statistics

The table shows the descriptive statistics for the sample of 68 insurers over the time period 2000-2020 with 768 observations. ΔCoVaR_{BAN}, ΔCoVaR_{INS} and $\Delta\text{CoVaR}_{NoFin}$ denote the CoVaR estimates with regard to the global banking sector (BAN), global insurance sector (INS) and global non-financial sector (NoFin). The values for the CoVaR are presented with negative sign, i.e. a higher value refers to a higher contribution to systemic risk. Total Assets, Total Liabilities and Total Debt are given in billion US-Dollar. All definitions and data sources are summarized in Appendix A.3.

4 Empirical Analysis

The following section provides the results of the baseline panel regression on the influence of insurance business diversification between life and non-life insurance on systemic risk in terms of financial contagion. The section also provides the outcome of several robustness checks and discusses policy implications based on the results.

4.1 Results

Table 3 presents the results of the panel regression. The results support Hypothesis I from the theoretical portfolio model, suggesting that diversified multiline insurers reduce systemic risk compared to monoline life and non-life insurers. In particular, the quadratic and linear terms regarding the life insurance ratio are significantly related to the systemic risk measures with different signs, underlining the existence of a u-shaped relation between insurance business diversification in terms of life and non-life insurance and systemic risk.

	Dependent variable:		
	ΔCoVaR$_{BAN}$	ΔCoVaR$_{INS}$	ΔCoVaR$_{NoFin}$
	(1)	(2)	(3)
$Life^2$	0.431**	0.484**	0.577**
	(0.021)	(0.032)	(0.012)
$Life$	−0.468**	−0.536**	−0.614***
	(0.019)	(0.017)	(0.007)
$Total\ Assets$	0.574***	0.569***	0.525***
	(0.000)	(0.000)	(0.000)
$Leverage$	−0.011	−0.005	−0.031
	(0.740)	(0.867)	(0.242)
$Non-Core\ Activities$	0.012	0.046*	0.055
	(0.728)	(0.052)	(0.189)
$Net-Claims-Ratio$	−0.038	−0.007	−0.057
	(0.500)	(0.904)	(0.409)
RoI	0.044	0.036	0.090
	(0.336)	(0.459)	(0.163)
RoE	−0.028	0.010	−0.002
	(0.396)	(0.739)	(0.962)
Year Fixed Effects	Y	Y	Y
Geo Fixed Effects	Y	Y	Y
Clustered Standard Errors	Y	Y	Y
Observations	768	768	768
R^2	0.732	0.720	0.700
Adjusted R^2	0.721	0.709	0.687
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: OLS Panel Regression

The table shows the results of the OLS panel regression on the model given by Equation 6 for the baseline sample of 68 international insurers from 2000 to 2020. Variable definitions and data sources are provided in Appendix A.3. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. Regression parameters are standardized with mean 0 and standard deviation 1. P-values are reported in parentheses. ΔCoVaR$_{BAN}$, ΔCoVaR$_{INS}$ and ΔCoVaR$_{NoFin}$ denote the CoVaR measures with regard to the global banking sector (BAN), global insurance sector (INS) and global non-financial sector (NoFin).

The results show that business diversification between life and non-life insurance can have an economic significant impact on the insurer's contribution to systemic risk. Monoline non-life insurers ($Life = 0$) reduce, on average, their contribution to systemic risk in the banking, insurance and non-financial sector by 0.47, 0.54 and 0.61 standard deviations, respectively, for an increase in the life insurance business allocation by 1 standard deviation.[8] Monoline life insurers ($Life = 1$) reduce, on average, their contribution to systemic risk in the banking, insurance and non-financial sector by 0.14, 0.15 and 0.21 standard deviations, respectively, for a reduction in the life insurance business allocation by 1 standard deviation.[9] Hence, systemic risk due to financial contagion from an insurer's financial distress is reduced more strongly if non-life insurers start to engage in the

[8] Due to the scaling of the regression parameters, the marginal effects on the dependent variables are expressed in terms of standard deviations. The marginal effect of the life business ratio can be 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 insurance business ratio. Hence, for $Life = 0$: $\Delta Y = \hat{\beta}_2$.

[9] A 1 Std. decrease in the life insurance business ratio results in a change of the life allocation from $L = 1$ to $L = 0.71$, which corresponds to $\Delta Y = -(2\hat{\beta}_1 0.71 + \hat{\beta}_2)\Delta Life$.

life insurance business than vice-versa, which is in line with Section 2.1, suggesting a less volatile life insurance business compared to non-life insurance. Moreover, large insurers are expected to cause significantly higher financial losses to the banking, insurance and non-financial sector, 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 seem to increase systemic risk in the insurance sector, but not with regard to the banking and non-financial sector. The effect of non-core activities suggests a stronger link regarding non-underwriting related activities like CDS transactions within the insurance sector than between insurers and banks. For differences in the insurer's underwriting portfolios (net claims ratio) and the operating profitability (RoI, RoE), no significant effects are found. In particular the magnitude of the effects of insurer's business diversification and size on systemic risk in the real economy approximated by the non-financial index (NoFin) is interesting. It underlines that insurers can propagate shocks directly to the real economy without going through the financial system. In that regard, the literature suggests the insurer's direct systemic link to the real economy to be particularly driven by two channels: i) a (short-term) lack of insurance coverage, which was a substantial systemic risk source in the cases of the two insurers AIG (2007-09) and HIH (2001), and ii) reduced funding of firms in the real economy (e.g. Bank of England (BoE) (2015a), European Systemic Risk Board (ESRB) (2015), Financial Stability Oversight Council (FSOC) (2013b), Bailey (2003)).

The significantly quadratic relation between systemic risk and the life insurance business ratio (Life) yields the potential for insurers to minimize their systemic risk contribution. The first order condition of the regression model in Equation 6 with regard to the life insurance business ratio yields a systemic risk minimizing business allocation given by $\alpha^* = \frac{-\hat{\beta}_2}{2\hat{\beta}_1}$, which is a minimum due to the second order condition with $\beta_1 > 0$ and $\beta_2 < 0$. Table 4 shows the systemic risk minimizing life insurance business allocations, which are consistently larger than 50% life insurance. This finding supports Hypothesis II, suggesting from a theoretical portfolio perspective that an overweight to the less volatile life insurance business is necessary to minimize systemic risk in terms of financial contagion. The regression analysis suggests that insurers can, on average, minimize their contribution to systemic risk in the banking, insurance and non-financial sector by seeking a life business allocation around 54%.

	BAN	INS	NoFin
α^*	0.54	0.55	0.53

Table 4: Systemic Risk minimizing Life Insurance Business Allocation

The table shows the average insurer's systemic risk minimizing life insurance business allocations α^*, based on the baseline panel regression model and coefficients given in Table 3, with regard to the banking (BAN), insurance (INS) and non-financial (NoFin) systems.

4.2 Robustness Checks

Appendix A.5 comprises the results of several robustness checks. Table 14 contains the correlation coefficients of the explanatory variables, showing only weak correlations across the variables. In order to lower the potential for endogeneity in terms of reverse causality between the insurer's systemic risk contribution and the insurer's contemporaneous business allocation between life and non-life insurance, the explanatory variables in the baseline regression are lagged by one year (e.g. Bierth et al. (2015), Weiß and Mühlnickel (2014)). As findings by Zimmer et al. (2018), Phillips et al. (1998) and Sommer (1996) show, policyholders pay less for insurance if the insurer is subject to higher distress risk. The resulting insolvency penalty would actually constitute a strong monetary incentive for insurers in the sample to become more diversified in order to reduce distress risk. However, the insurer's business allocation in the sample is relatively persistent over time, suggesting that the level of distress risk, and hence the resulting level of financial contagion and systemic risk, does not play a major role for the insurer's decision to diversify its insurance business.

Moreover, several different model specifications are tested. Specifying insurer's size through total liabilities (Table 15), and specifying leverage through a more bank-oriented definition in terms of the debt-to-asset ratio (Table 16), support the results of the baseline regression. Including pure monoline life and non-life insurers in the sample reduces the significance in the effects of the explanatory variables in the baseline regression model as expected (Table 17). These monoline insurers do not change their business model over time and therefore do not provide any variation in the life insurance business ratio that can be used for estimating the marginal effect of insurance business diversification on systemic risk. However, in order to challenge the role of insurance business diversification for systemic risk as suggested by the baseline regression, a binary dummy variable is introduced, indicating a value of 0 for undiversified life or non-life insurers, and a value of 1 for multiline insurers diversifying across both insurance lines. First, a t-test on the equality of

ΔCoVaR mean values between undiversified and diversified insurers is conducted (Table 18). The results show that diversified insurers contribute, on average, significantly less to systemic risk than undiversified insurers. Second, a panel regression with the diversification dummy variable instead of the life insurance business ratio is conducted (Table 5). The effect of the dummy variable is significantly negative, showing that diversified insurers, on average, are less associated with systemic risk in the banking, insurance and non-financial sector than undiversified insurers. The result underlines the outcome of the baseline panel regression on the marginal impact of insurance business diversification on insurer's contribution to systemic risk, indicating that insurers can, on average, significantly reduce systemic risk through business diversification.

	Dependent variable:		
	ΔCoVaR$_{BAN}$	ΔCoVaR$_{INS}$	ΔCoVaR$_{NoFin}$
	(1)	(2)	(3)
$Diversification$	-0.089^{**}	-0.087^{*}	-0.103^{**}
	(0.032)	(0.075)	(0.033)
$Total\ Assets$	0.526^{***}	0.563^{***}	0.543^{***}
	(0.000)	(0.000)	(0.000)
$Leverage$	-0.005	0.003	-0.034
	(0.889)	(0.924)	(0.331)
$Non-Core\ Activities$	-0.027	0.010	0.013
	(0.488)	(0.753)	(0.754)
$Net-Claims-Ratio$	0.010	0.006	-0.038
	(0.715)	(0.828)	(0.305)
RoI	-0.018	-0.015	0.022
	(0.568)	(0.616)	(0.566)
RoE	0.028	0.036	0.015
	(0.284)	(0.126)	(0.544)
Year Fixed Effects	Y	Y	Y
Geo Fixed Effects	Y	Y	Y
Clustered SE	Y	Y	Y
Observations	1,722	1,722	1,722
R^2	0.660	0.672	0.615
Adjusted R^2	0.654	0.667	0.609
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Robustness Check with Diversification Dummy

The table shows the results of the OLS panel regression on the model given by Equation 6 from 2000 to 2020, but with a dummy variable indicating insurer's diversification extent. The dummy variable is denoted by $Diversification$ and has the value 0 for economically undiversified life or non-life insurers (with at least 85% premium income from life or non-life insurance), and the value 1 for diversified insurers. Variable definitions and data sources are provided in Table 8. List of insurers is given in Table 13. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. Regression parameters are standardized with mean 0 and standard deviation 1. P-values are reported in parentheses. ΔCoVaR$_{BAN}$, ΔCoVaR$_{INS}$ and ΔCoVaR$_{NoFin}$ denote the CoVaR measures with regard to the global banking sector (BAN), global insurance sector (INS) and global non-financial sector (NoFin).

4.3 Policy Implications

The theoretical and empirical findings suggest that 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 financial consequences of their distress to other institutions. For macroprudential insurance regulation, the findings suggest that undiversified monoline insurers should be monitored more closely than diversified multiline insurers. The extent of insurer's business diversification could serve as an additional indicator for assessing the systemic relevance of insurers and to allocate the supervisor's monitoring resources. It could be included in the current indicator-based model used by the IAIS for the "individual insurer monitoring" exercise within the holistic systemic risk framework (International Association of Insurance Supervisors (IAIS) (2019b), International Association of Insurance Supervisors (IAIS) (2018)). For example, based on the 2016 list of global systemically important insurers (Financial Stability Board (2016)), insurers like Prudential Financial would pose a greater threat to financial stability as they focus their insurance business mainly on one insurance line compared to the other, more diversified insurers on that list. Thus, taking into account the systemic risk reducing effect of insurance business diversification can help to allocate the supervisor's monitoring efforts more efficiently and to reduce regulatory costs for diversified multiline insurers.

However, the question arises if all insurers should be exogenously incentivized to diversify their business 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. The central assumption in these studies is that higher homogenization across institutions increases the correlation of their exposures. However, this assumption does not seem to be appropriate for the insurance sector, as insurance claims are typically uncorrelated as the central condition for a risk pooling effect. Moreover, claims related to catastrophic events, for example earthquakes, are correlated only among certain policyholders in the affected region, and the insured losses are mainly reinsured, which reduces the potential for common underwriting exposures across insurers. Therefore, considering the systemic risk reducing effect of insurance business diversification could be a valuable extension in the macroprudential toolbox to mitigate systemic risk.

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 insurer with the same size, then, the monoline insurer typically has a higher level of diversification within its specific line of business, as it sells more similar insurance contracts to different policyholders compared to the multiline insurer. The larger risk pool, and hence higher economies of scale with respect to risk taking, would enable 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. However, multiline insurers could benefit from economies of scope, as they diversify across insurance lines which lowers their distress risk. Then, given the insolvency penalty on insurance markets (e.g. Zimmer et al. (2018), Phillips et al. (1998), Sommer (1996)), multiline insurers could charge higher premiums for insurance contracts due to lower insolvency risk compared to monoline insurers. Hence, the implications of insurance business diversification on insurance markets seem to be substantially characterized by a tradeoff between economies of scale, i.e. a higher degree of diversification within insurance lines, and economies of scope, i.e. a higher degree of diversification across insurance lines. Future research should study this diversification tradeoff in order to assess the potential market implications that could arise from a systemic risk reducing level of insurance business diversification across insurers.

5 Conclusion

This paper studies the influence of insurance business diversification between life and non-life insurance on the insurer's contribution to systemic risk in terms of financial contagion, i.e. the spillover of losses from financially distressed insurers to other institutions. Evidence on the volatility and correlation of cash flows associated with life and non-life insurance suggest a financially stabilizing diversification potential for multiline insurers active in both insurance lines. Based on a theoretical portfolio model, it is shown that diversified multiline insurers can reduce financial contagion risk in terms of counterparty credit risk, which is an important channel for systemic risk. The model suggests a u-shaped relation between insurance business diversification in terms of life and non-life insurance and systemic risk, and more specifically, it suggests a systemic risk minimizing insurance business allocation with an overweight to the less volatile life insurance business.

The empirical analysis based on a sample of 68 insurers from 2000 to 2020 tests the theoretical hypotheses. The insurer's contribution to systemic risk is estimated with the ΔCoVaR, based on the banking system, the insurance system and the non-financial system in order to study the direct consequences of the insurer's financial distress on the real economy. The empirical results underline the u-shaped relation between insurance business diversification in terms of life and non-life insurance and systemic risk in terms of financial contagion. The results suggest that monoline life and monoline non-life insurers contribute, on average, more to systemic risk than diversified multiline insurers. More specifically, insurers with an insurance business allocation in the range of 54% life insurance minimize, on average, their contribution to systemic risk in terms of financial contagion. For macroprudential insurance regulation, the findings suggest that undiversified monoline insurers should be monitored more closely than diversified multiline insurers. Since insurance business diversification between life and non-life insurance has not been taken into account so far by macroprudential insurance regulation, supervisors could use the insurer's level of business diversification as an additional indicator for assessing the systemic relevance of insurers. The extension of the macroprudential toolbox in that regard could reduce systemic risk stemming from financially distressed insurers and save regulatory costs by supporting supervisors in allocating their monitoring efforts.

A Appendix

A.1 Underwriting Cash Flows

Table 6 shows the data used for the cash flow analysis between life and non-life insurance in Section 2.1. All monoline life and monoline non-life insurers are selected from SNL Financial (S&P Market Intelligence) over the time period of 2005-2019. The sample is corrected for dead-firms and for all insurers for which underwriting-related cash flow data is not available over the full time period. After cleaning the sample, annual data is collected in US-$ for a sample of 56 insurers, which consists of 42 non-life (P&C) insurers and 14 life (L&H) insurers. Table 7 shows the list of insurers used for the cash flow analysis.

Variable	Definition	Data Source
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.	SNL Key: 286130
L&H Net Premiums Earned	Life insurance and Accident & Health premiums earned, net of reinsurance. This variable is used to classify life insurance business.	SNL Key: 286131
P&C Losses & LAE	Expenses of settling Property & Casualty insurance claims related to written policies, net of reinsurance. Expenses include those necessary for the indemnification of the insured, as well as those expenses incurred in the course of investigating and settling claims.	SNL Key: 286142
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.	SNL Key: 286143

Table 6: Variables and Data Sources for the Cash Flow Analysis

Entity Name	Entity ID (SNL)	Region
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 7: Insurer Sample for the Cash Flow Analysis

A.2 The Counterparty's Expected Loss

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

$$R = \alpha\, R_L + (1-\alpha)\, R_{NL}. \tag{7}$$

where R_L and R_{NL} denote the normally distributed equity cash flows generated by the life (L) and non-life (NL) 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 equity cash flow is independent from α. The first order condition of the counterparty's expected loss (Equation 1) with regard to the business allocation parameter α yields

$$\begin{aligned}
\frac{\partial EL}{\partial \alpha} &= (D-\mu_R)\,\frac{\partial \Phi(z)}{\partial \alpha} + \frac{\partial \sigma_R}{\partial \alpha}\,\Phi'(z) + \sigma_R\,\frac{\partial \Phi'(z)}{\partial \alpha} \\
&= (D-\mu_R)\,\Phi'(z)\,\frac{\partial z}{\partial \alpha} + \frac{1}{2\sigma_R}\,\frac{\partial \sigma_R^2}{\partial \alpha}\,\Phi'(z) - \sigma_R\, z\,\Phi'(z)\,\frac{\partial z}{\partial \alpha} \\
&= \frac{1}{2\sigma_R}\,\Phi'(z)\,\frac{\partial \sigma_R^2}{\partial \alpha}
\end{aligned} \tag{8}$$

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 and a risk minimum for a sufficiently small correlation between both insurance lines, which is in line with the low correlation levels as suggested in Section 2.1. The risk minimizing allocation is given by

$$\begin{aligned}
\frac{\partial \sigma_R^2}{\partial \alpha} &= 0 \\
\alpha^* &= \frac{\sigma_{NL}^2 - \sigma_L\,\sigma_{NL}\,\rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\,\sigma_L\,\sigma_{NL}\,\rho}
\end{aligned} \tag{9}$$

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.3 Variables and Data for the Regression Analysis

Table 8 provides the overview of the variables and data for the baseline panel regression.

Variable	Definition	Data Source
Dependent variables		
ΔCoVaR	Difference between a system's Value-at-Risk (VaR) conditional on a particular insurer being in distress at its 5% daily return quantile and the system's VaR conditional on that insurer's median state. Annual mean values of the weekly estimates in a given year are taken as the dependent variable in the regression analysis.	Datastream, SNL Financial (S&P Market Intelligence)
Systems considered	MSCI World Banking Index	Datastream
	Global Insurance System	Own calculation
	Datastream World Non-Financial Index	Datastream
Explanatory variables		
Life Insurance Ratio	Ratio of net premiums earned in life-health business to total net premiums earned (life and non-life). It is net of reinsurance.	SNL Key: 132544, 134652
Net-Claims-Ratio	Ratio of total net claims and benefits to total net premiums earned.	SNL Key: 245623, 134652
Non-Core Activities	Ratio of total liabilities to total insurance reserves.	SNL Key: 263009, 263004
Leverage	Ratio of total net premiums earned to policyholder surplus as difference between total assets and total liabilities.	SNL Key: 132541, 132544, 132264, 263009
Debt to Asset Ratio	Ratio of total debt to total assets.	SNL Key: 263008, 132264
Total Assets	Natural logarithm of total assets.	SNL Key: 132264
Total Liabilities	Natural logarithm of total liabilities.	SNL Key: 263009
RoI	Ratio of absolute investment income to total assets.	SNL Key: 245211, 132264
RoE	Return on Equity.	SNL Key: 329316

Table 8: Variables and Data Sources for the Baseline Regression

Data is mainly collected from SNL Financial (S&P Market Intelligence). Missing data is added from Datastream by means of ISIN matches. Data is collected in US-$.

Table 9 shows the insurer sample for the baseline panel regression, and Table 10 shows the geographic distribution of the insurers.

Name	ISIN	Name	ISIN
1 Aegon N.V.	NL0000303709	35 Loews Corporation	US5404241086
2 Allstate Corporation	US0200021014	36 Maiden Holdings Ltd.	BMG5753U1128
3 Assicurazioni Generali S.p.A.	IT0000062072	37 Manulife Financial Corporation	CA56501R1064
4 Atlantic American Corporation	US0482091008	38 MetLife, Inc.	US59156R1086
5 Aviva plc	GB0002162385	39 Mutual Benefits Assurance plc	NGMBENEFT000
6 AvivaSA Emeklilik ve Hayat AS	TRECUHE00018	40 National Reinsurance Corporation of the Philippines	PHY6251L1099
7 AXA SA	FR0000120628	41 Niger Insurance plc	NGNIGERINS04
8 Axis Capital Holdings Limited	BMG0692U1099	42 NN Group N.V.	NL0010773842
9 Bâloise Holding AG	CH0012410517	43 Ping An Insurance (Group) Company of China, Ltd.	CNE1000003X6
10 Baoviet Holdings	VN000000BVH3	44 Pozavarovalnica Sava d.d.	SI0021110513
11 Beazley plc	GB00BYQ0JC66	45 PT Panin Insurance	ID1000094907
12 Britam Holdings plc	KE2000002192	46 PZU Group	PLPZU0000011
13 Central Reinsurance Corporation	TW0002851003	47 Rand Merchant Investment Holdings Limited	ZAE000210688
14 China Pacific Insurance Group Co., Ltd.	CNE1000008M8	48 RheinLand Holding AG	DE0008415100
15 China Reinsurance (Group) Corporation	CNE100002342	49 Royal Exchange plc	NGROYALEX007
16 Chubb Limited	CH0044328745	50 Sampo OYJ	FI0009003305
17 Cincinnati Financial Corporation	US1720621010	51 Samsung Fire & Marine Insurance Co., Ltd.	KR7000810002
18 Citizens, Inc.	US1747401008	52 Scor SE	FR0010411983
19 DB Insurance Co., Ltd.	KR7005830005	53 Societa Cattolica di Assicurazione S.p.A.	IT0000784154
20 Discovery Holdings Ltd.	ZAE000022331	54 Société Tunisienne d'Assurances et de Réassurances	TN0006060016
21 E-L Financial Corporation Limited	CA2685751075	55 Storebrand ASA	NO0003053605
22 Enstar Group Ltd.	BMG3075P1014	56 Suncorp Group Ltd.	AU000000SUN6
23 European Reliance General Insurance	GRS277023008	57 Swiss Life Holding AG	CH0014852781
24 Genworth Financial, Inc.	US37247D1063	58 Swiss Re AG	CH0126881561
25 Grupo Catalana Occidente SA	ES0116920333	59 The People's Insurance Company (Group) of China Ltd.	CNE100001MK7
26 Hanover Insurance Group	US4108671052	60 Tiptree Financial A	US88822Q1031
27 Hartford Financial Services Group, Inc.	US4165151048	61 Topdanmark A/S	DK0060477503
28 Helvetia Holding AG	CH0466642201	62 UNIQA Insurance Group AG	AT0000821103
29 Heungkuk Fire & Marine Insurance Co., Ltd.	KR7000540005	63 United Fire Group Inc.	US9103401082
30 Horace Mann Educators Co.,	US4403271046	64 Vaudoise Assurances Holding SA	CH0021545667
31 Jubilee Holdings Ltd.	KE0000000273	65 Wafa Assurance SA.	MA0000010928
32 Kemper Corporation	US4884011002	66 Wüstenrot & Württembergische AG	DE0008051004
33 Korean Reinsurance Company	KR7003690005	67 Zavarovalnica Triglav d.d.	SI0021111651
34 La Société Tunisienne de Reassurance	TN0007380017	68 Zurich Insurance Group AG	CH0011075394

Table 9: List of Insurers in the Baseline Regression Sample from 2000-2020

Geography	Fraction
Europe	39.7%
United States and Canada	26.5%
Asia-Pacific	19.1%
Africa	14.7%

Table 10: Geographic Distribution of Insurers in the Baseline Regression Sample

A.4 Estimation of Systemic Risk

The ΔCoVaR by Adrian and Brunnermeier (2016) is defined as the system's increase in tail risk when the particular insurer under consideration becomes financially distressed compared to the insurer's median state. The estimation of the ΔCoVaR capturing the time-varying tail dependence between the insurer and the system is based on quantile regressions using the state variables as given in Table 11. Daily observations of insurer's stock returns are collapsed into weekly frequency. The estimation of the dependence of insurer i's return with the state variables and the systems is conducted on the total available time horizon from Jan 2000 to Dec 2020. The result is a weekly estimate for the ΔCoVaR. The mean value of the weekly estimates in a given year is then used in the panel regression for the insurer's yearly systemic risk contribution.

State Variable	Data
US 3M T-Bill rate	weekly data, FRB H15
US Treasury Yield Spread (10Y-3M)	weekly data, FRB H15
Short-term TED spread	weekly spread between 3-Month LIBOR and 3-Month Treasury Bill rate, FRED
Credit Spread	weekly change in credit spread between Moody's Baa-rated bonds and ten-year Treasury rate, FRED
S&P500	weekly return, Datastream
VIX	weekly data, FRED

Table 11: State Variables for ΔCoVaR Estimation

Details on the estimation: Adrian and Brunnermeier (2016) and Bisias et al. (2012).

1. The Global Banking System (INS)

The global banking system is approximated by the MSCI World Banking Index, which is a public market index containing stocks from 71 banks across 23 markets.

2. The Global Insurance System (INS)

The global insurance system is represented by a constructed index of 159 international insurers (Table 13, explained in Section 3.1). For each insurer under consideration for the ΔCoVaR estimation, a separate return index of the insurance system is calculated, based on a market capitalization weighted return index of all other insurers in the system. Hence, it prevents from a double counting of the specific insurer's return and a constructed correlation between the insurer's tail risk and the system's tail risk.

The index return series is calculated similar to Bisias et al. (2012) as follows: MC_t^i stands for the market capitalization of insurer i at day 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 insurer $i \in \{1, ..., N\}$ at day t is given as the market capitalization weighted average of the remaining institutions' returns from time $t-1$ to t:

$$r_t^{S|i} = \sum_{s \in S \setminus \{i\}} \frac{MC_{t-1}^s}{\sum_{j \in S \setminus \{i\}} MC_{t-1}^j} \left(\frac{P_t^s}{P_{t-1}^s} - 1\right) \tag{10}$$

3. The Global Non-Financial System (NoFin)

The non-financial system is represented by the Datastream World Non-Financial Index, consisting of 5277 firms from a broad spectrum of industrial sectors and geographical regions. Table 12 gives an overview of the geographic and sectoral distribution of the index.

Geographic Distribution		**Sectoral Distribution**	
Country	Fraction	Sector	Fraction
Japan	16%	Software and Computer Services	7%
U.S.	15%	Travel and Leisure	5%
United Kingdom	5%	Food	5%
France	4%	Pharmaceuticals and Biotechnology	5%
Germany	4%	General Retailers	4%
Canada	4%	Electricity	4%
India	3%	Industrial Transportation	4%
Italy	2%	Construction and Materials	3%
Australia	2%	Health Care Equipment and Services	3%

Table 12: Composition of the Datastream NoFin Index

Relative weights of countries and industrial sectors in the Datastream World Non-Financial Index (NoFin) as of January 2021.

Name	ISIN	Name	ISIN
1 Admiral Group Plc	GB00B02J6398	81 Loews Corporation	US5404241086
2 Aegon N.V.	NL0000303709	82 Maiden Holdings Ltd.	BMG5753U1128
3 Aflac Inc.	US0010551028	83 Manulife Financial Corporation	CA56501R1064
4 AIA Group Ltd.	HK0000069689	84 Markel Corporation	US5705351048
5 Alleghany Corporation	US0171751003	85 MBIA Inc.	US55262C1009
6 Allstate Corporation	US0200021014	86 Medibank Private Ltd.	AU000000MPL3
7 Ambac Financial Group, Inc.	US0231398845	87 Mercuries Life Insurance Co., Ltd.	TW0002867009
8 AMERISAFE, Inc.	US03071H1005	88 Mercury General Corporation	US5894001008
9 Anicom Holdings, Inc.	JP3122440005	89 MetLife, Inc.	US59156R1086
10 Arch Capital Group Ltd.	BMG0450A1053	90 Münchener Rück AG	DE0008430026
11 Assicurazioni Generali S.p.A.	IT0000062072	91 Mutual Benefits Assurance plc	NGMBENEFT000
12 Assurant, Inc.	US04621X1081	92 N.E.M. Insurance plc	NGNEM0000005
13 Assured Guaranty Ltd.	BMG0585R1060	93 National Reinsurance Corporation of the Philippines	PHY6251L1099
14 Atlantic American Corporation	US0482091008	94 New China Life Insurance Co. Ltd.	CNE1000019Y0
15 Atlantic Insurance Company Public Ltd.	CY0006010314	95 NIB Holdings Ltd.	AU000000NHF0
16 Aviva plc	GB0002162385	96 Niger Insurance plc	NGNIGERINS04
17 AvivaSA Emeklilik ve Hayat AS	TRECUHE00018	97 NMI Holdings	US6292093050
18 AXA SA	FR0000120628	98 NN Group N.V.	NL0010773842
19 Axis Capital Holdings Limited	BMG0692U1099	99 Personal Group Holdings plc	GB0002760279
20 Bâloise Holding AG	CH0012410517	100 Petrolimex Insurance Corporation	VN000000PGI2
21 Bangkok Insurance Public Company Limited	TH0042010007	101 Phoenix Group Holdings plc	GB00BGXQNP29
22 Bangkok Life Assurance Public Company Limited	TH1016010007	102 Ping An Insurance (Group) Company of China, Ltd.	CNE1000003X6
23 BaoMinh Insurance Corp	VN000000BMI0	103 Pozavarovalnica Sava d.d.	SI0021110513
24 Baoviet Holdings	VN000000BVH3	104 Primerica, Inc.	US74164M1080
25 Beazley plc	GB00BYQ0JC66	105 Principal Financial Group, Inc.	US74251V1026
26 Britam Holdings plc	KE2000002192	106 ProAssurance Corporation	US74267C1062
27 Central Reinsurance Corporation	TW0002851003	107 Progressive Corporation	US7433151039
28 Chesnara plc	GB00B00FPT80	108 Protective Insurance B	US74368L2034
29 China Pacific Insurance Group Co., Ltd.	CNE1000008M8	109 Protector Forsikring ASA	NO0010209331
30 China Reinsurance (Group) Corporation	CNE100002342	110 Prudential Financial, Inc.	US7443201022
31 Chubb Limited	CH0044328745	111 Prudential plc	GB0007099541
32 Cincinnati Financial Corporation	US1720621010	112 PT Panin Insurance	ID1000094907
33 Citizens, Inc.	US1747401008	113 PVI Holdings	VN000000PVI1
34 Coface SA	FR0010667147	114 PZU Group	PLPZU0000011
35 DB Insurance Co., Ltd.	KR7005830005	115 Radian Group Inc.	US7502361014
36 Dhipaya Insurance Public Company Limited	TH0588010Z04	116 Rand Merchant Investment Holdings Limited	ZAE000210688
37 Direct Line Insurance Group plc	GB00BY9D0Y18	117 Reinsurance Group of America, Incorporated	US7593516047
38 Discovery Holdings Ltd.	ZAE000022331	118 RenaissanceRe Holdings Ltd.	BMG7496G1033
39 E-L Financial Corporation Limited	CA2685751075	119 RheinLand Holding AG	DE0008415100
40 Employers Holdings, Inc.	US2922181043	120 RLI Corporation	US7496071074
41 Enstar Group Ltd.	BMG3075P1014	121 Royal Exchange plc	NGROYALEX007
42 Essent Group Ltd.	BMG3198U1027	122 RSA Insurance Group plc	GB00BKKMKR23
43 European Reliance General Insurance	GRS277023008	123 Safety Insurance Group	US78648T1007
44 Everest Re Group Ltd.	BMG3223R1088	124 Sampo OYJ	FI0009003305
45 Fairfax Financial Holdings Ltd.	CA3039011026	125 Samsung Fire & Marine Insurance Co., Ltd.	KR7000810002
46 FBD Holdings plc	IE0003290289	126 Samsung Life Insurance Co., Ltd.	KR7032830002
47 Federated National Holding Company	US31431B1098	127 Scor SE	FR0010411983
48 Fidelity National Financial, Inc.	US31620R3030	128 Selective Insurance Group	US8163001071
49 First Acceptance Insurance Company, Inc.	US3184571087	129 Shinkong Insurance Co., Ltd.	TW0002850005
50 First American Financial Corporation	US31847R1023	130 Singapore Reinsurance Corporation Limited	SG1J71891696
51 First Insurance Co., Ltd.	TW0002852001	131 Societa Cattolica di Assicurazione S.p.A.	IT0000784154
52 Genworth Financial, Inc.	US37247D1063	132 Société Tunisienne d'Assurances et de Réassurances	TN0006060016
53 Greenlight Capital RE Ltd.	KYG4095J1094	133 Stewart Information Services	US8603721015
54 Grupo Catalana Occidente SA	ES0116920333	134 Storebrand ASA	NO0003053605
55 Hanover Insurance Group	US4108671052	135 Suncorp Group Ltd.	AU000000SUN6
56 Hanwha Life Insurance Co., Ltd.	KR7088350004	136 Swiss Life Holding AG	CH0014852781
57 Hartford Financial Services Group, Inc.	US4165151048	137 Swiss Re AG	CH0126881561
58 HCI Group, Inc.	US40416E1038	138 Syn Mun Kong Insurance Public Company Limited	TH0239A10Z06
59 Helios Underwriting plc	GB00B23XLS45	139 Taiwan Fire & Marine Insurance Co., Ltd.	TW0002832003
60 Helvetia Holding AG	CH0466642201	140 The People's Insurance Company (Group) of China Ltd.	CNE100001MK7
61 Heritage Insurance Holdings, Inc.	US42727J1025	141 Tiptree Financial A	US88822Q1031
62 Heungkuk Fire & Marine Insurance Co., Ltd.	KR7000540005	142 Topdanmark A/S	DK0060477503
63 Hiscox Ltd.	BMG4593F1389	143 Travelers Inc.	US89417E1091
64 Horace Mann Educators Co.,	US4403271046	144 Trupanion, Inc.	US8982021060
65 Hyundai Marine & Fire Insurance Co., Ltd.	KR7001450006	145 Unico American Corporation	US9046071083
66 Independence Holding Co.	US4534403070	146 Union Insurance Co., Ltd.	TW0002816006
67 Insurance Australia Group Ltd.	AU000000IAG3	147 UNIQA Insurance Group AG	AT0000821103
68 Intact Financial Corporation	CA45823T1066	148 United Fire Group Inc.	US9103401082
69 Investors Title Co.	US4618041069	149 United Insurance Holdings Corporation	US9107101027
70 James River Group Holdings Ltd.	BMG5005R1079	150 Universal Insurance Holdings, Inc.	US91359V1070
71 Jubilee Holdings Ltd.	KE0000000273	151 Unum Group	US91529Y1064
72 Just Group plc	GB00BCRX1J15	152 Vaudoise Assurances Holding SA	CH0021545667
73 Kansas City Life Insurance Co.	US4848362004	153 Vietnam National Reinsurance Corporation	VN000000VNR7
74 Kemper Corporation	US4884011002	154 Voya Financial Inc.	US9290891004
75 Kingstone Companies, Inc.	US4967191051	155 W.R. Berkley Corporation	US0844231029
76 Kingsway Financial Services, Inc.	US4969042021	156 Wafa Assurance SA.	MA0000010928
77 Korean Reinsurance Company	KR7003690005	157 Wüstenrot & Württembergische AG	DE0008051004
78 La Société Tunisienne de Reassurance	TN0007380017	158 Zavarovalnica Triglav d.d.	SI0021111651
79 Lancashire Holdings Ltd.	BMG5361W1047	159 Zurich Insurance Group AG	CH0011075394
80 Legal & General Group plc	GB0005603997		

Table 13: List of Insurers representing the Global Insurance System for the Estimation of ΔCoVaR

A.5 Robustness Checks: Supplementary Tables

The following tables show the outcomes of several robustness checks.

Total Assets	Total Liabilities	Net Claims Ratio	RoI	Life Insurance Ratio	Debt to Asset Ratio	Leverage	Non-Core Activities	RoE
1	0.99	0.44	-0.03	0.36	0.13	-0.01	0.03	-0.03
	1	0.45	-0.03	0.37	0.13	-0.01	0.04	-0.03
		1	0.32	0.47	-0.06	-0.03	-0.04	-0.06
			1	0.02	0.06	-0.15	-0.09	0.31
				1	-0.01	0.18	0.13	-0.04
					1	-0.11	0.20	-0.03
						1	-0.06	-0.10
							1	0.21
								1

Table 14: Correlation Coefficients of the Explanatory Variables

	Dependent variable:		
	ΔCoVaR$_{BAN}$	ΔCoVaR$_{INS}$	ΔCoVaR$_{NoFin}$
	(1)	(2)	(3)
$Life^2$	0.470**	0.521**	0.611***
	(0.013)	(0.023)	(0.009)
$Life$	−0.508**	−0.575**	−0.650***
	(0.011)	(0.012)	(0.005)
$Total\ Liabilities$	0.585***	0.577***	0.532***
	(0.000)	(0.000)	(0.000)
$Leverage$	−0.022	−0.016	−0.042
	(0.468)	(0.561)	(0.101)
$Non-Core\ Activities$	0.008	0.042*	0.051
	(0.827)	(0.080)	(0.223)
$Net-Claims-Ratio$	−0.054	−0.020	−0.070
	(0.346)	(0.714)	(0.314)
RoI	0.061	0.051	0.104
	(0.200)	(0.295)	(0.108)
RoE	−0.032	0.007	−0.005
	(0.328)	(0.835)	(0.889)
Year Fixed Effects	Y	Y	Y
Geo Fixed Effects	Y	Y	Y
Clustered SE	Y	Y	Y
Observations	768	768	768
R^2	0.732	0.719	0.698
Adjusted R^2	0.721	0.707	0.685
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 15: Robustness Check: Size as Total Liabilities

The table shows the results of the OLS panel regression on the model given by Equation 6 from 2000 to 2020, but with total liabilities instead of total assets. Variable definitions and data sources are provided in Appendix A.3. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. Regression parameters are standardized with mean 0 and standard deviation 1. P-values are reported in parentheses. ΔCoVaR$_{BAN}$, ΔCoVaR$_{INS}$ and ΔCoVaR$_{NoFin}$ denote the CoVaR measures with regard to the global banking sector (BAN), global insurance sector (INS) and global non-financial sector (NoFin).

	Dependent variable:		
	ΔCoVaR$_{BAN}$	ΔCoVaR$_{INS}$	ΔCoVaR$_{NoFin}$
	(1)	(2)	(3)
$Life^2$	0.440**	0.457**	0.592***
	(0.017)	(0.040)	(0.009)
$Life$	−0.473**	−0.510**	−0.631***
	(0.015)	(0.019)	(0.005)
$Total\ Assets$	0.600***	0.611***	0.544***
	(0.000)	(0.000)	(0.000)
$Leverage : D/A$	−0.012	−0.064	−0.014
	(0.855)	(0.347)	(0.802)
$Non-Core\ Activities$	0.016	0.061**	0.061
	(0.661)	(0.036)	(0.194)
$Net-Claims-Ratio$	−0.058	−0.040	−0.068
	(0.320)	(0.497)	(0.327)
RoI	0.063	0.063	0.103*
	(0.128)	(0.144)	(0.097)
RoE	−0.032	−0.004	−0.001
	(0.236)	(0.861)	(0.965)
Year Fixed Effects	Y	Y	Y
Geo Fixed Effects	Y	Y	Y
Clustered SE	Y	Y	Y
Observations	775	775	775
R^2	0.736	0.722	0.699
Adjusted R^2	0.725	0.711	0.686
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 16: Robustness Check: Leverage as Debt-to-Asset Ratio

The table shows the results of the OLS panel regression on the model given by Equation 6 from 2000 to 2020, but with leverage as debt-to-asset ratio. Variable definitions and data sources are provided in Appendix A.3. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. Regression parameters are standardized with mean 0 and standard deviation 1. P-values are reported in parentheses. ΔCoVaR$_{BAN}$, ΔCoVaR$_{INS}$ and ΔCoVaR$_{NoFin}$ denote the CoVaR measures with regard to the global banking sector (BAN), global insurance sector (INS) and global non-financial sector (NoFin).

	Dependent variable:		
	$\Delta \text{CoVaR}_{BAN}$	$\Delta \text{CoVaR}_{INS}$	$\Delta \text{CoVaR}_{NoFin}$
	(1)	(2)	(3)
$Life^2$	0.331*	0.293	0.383*
	(0.078)	(0.188)	(0.081)
$Life$	−0.365*	−0.346	−0.433*
	(0.067)	(0.141)	(0.058)
$Total\ Assets$	0.538***	0.580***	0.561***
	(0.000)	(0.000)	(0.000)
$Leverage$	−0.001	0.010	−0.027
	(0.988)	(0.786)	(0.434)
$Non-Core\ Activities$	−0.025	0.013	0.016
	(0.528)	(0.693)	(0.705)
$Net-Claims-Ratio$	0.018	0.021	−0.025
	(0.548)	(0.426)	(0.495)
RoI	−0.018	−0.015	0.023
	(0.570)	(0.627)	(0.559)
RoE	0.027	0.037	0.015
	(0.296)	(0.126)	(0.566)
Year Fixed Effects	Y	Y	Y
Geo Fixed Effects	Y	Y	Y
Clustered SE	Y	Y	Y
Observations	1,722	1,722	1,722
R^2	0.659	0.672	0.615
Adjusted R^2	0.653	0.666	0.608
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 17: Robustness Check: Global Insurance System as Sample

The table shows the results of the OLS panel regression on the model given by Equation 6 from 2000 to 2020, but with the global insurance system as sample (Table 13). The sample includes pure undiversified monoline life ($Life = 1$) and non-life ($Life = 0$) insurers and diversifying multiline insurers engaging in both, life and non-life insurance. Variable definitions and data sources are provided in Table 8. All panel regressions are estimated with year and geographic fixed effects and with clustered standard errors at the insurer-level. Regression parameters are standardized with mean 0 and standard deviation 1. P-values are reported in parentheses. $\Delta \text{CoVaR}_{BAN}$, $\Delta \text{CoVaR}_{INS}$ and $\Delta \text{CoVaR}_{NoFin}$ denote the CoVaR measures with regard to the global banking sector (BAN), global insurance sector (INS) and global non-financial sector (NoFin).

Systemic Risk Measure	Undiversified	Diversified
$\Delta \text{CoVaR}_{BAN}$	2.519320e-09	6.511318e-10***
$\Delta \text{CoVaR}_{INS}$	2.429158e-09	2.698513e-10***
$\Delta \text{CoVaR}_{NoFin}$	1.672022e-09	1.841832e-10***

Table 18: t-test on the Equality of scaled ΔCoVaR mean values

The table shows the test of differences between the mean values of the ΔCoVaR with regard to the banking (BAN), insurance (INS) and non-financial (NoFin) systems for undiversified and diversified insurers. An unpaired t-test that assumes unequal variances across groups is conducted. Since insurer's size is a strong determinant for the insurer's systemic risk contribution, each insurer's ΔCoVaR estimate is scaled by the insurer's size in terms of total assets. Life and non-life insurers which have at least 85% of their premium income stemming from life or non-life insurance business are considered as economically undiversified insurers, the residual insurers are considered as diversified. The means between undiversified and diversified insurers are significantly different at the 1% level.

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