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Diversification of Business Activities and Systemic Risk*

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Abstract

This paper provides empirical evidence that financial institutions with more-diversified business activities can have a lower contribution to systemic risk. More specifically, we show that insurance holdings with a diversified business mix of traditional life and non-life insurance business contribute less to systemic risk than monoline insurers. We motivate this finding with a portfolio style model in which a diversified business mix reduces counterparty credit risk triggered by an insurance holding. In the subsequent empirical analysis with firm-level data from 74 international insurance companies from 2007 to 2015, we find that, on average, insurance holdings with a fraction of slightly more than 50% of premiums written in life insurance exhibit the smallest contribution to systemic risk. This fraction tends to increase with an insurer's investment volatility, leverage ratio, and the scope of active reinsurance assumed. Our findings have important implications for the design of macro-prudential policies.

Keywords: Financial Institutions, Systemic Risk, Diversification

JEL Classification: G01, G22, G23, G28

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1 Introduction

The recent financial crisis 2007-08 was a prime example for large risk spillovers across financial institutions, resulting in a severe heightening of systemic risk. In this context, the role of diversification at financial institutions has been highly disputed: On the one hand, diversification can make institutions more stable on an individual basis by lowering, for example, their income volatility. On the other hand, it can increase their common exposures across the financial sector as a whole, which may increase the likelihood of contagion and joint failures (as shown and emphasized, e.g., by Allen and Gale (2001), Wagner (2010), and Battiston et al. (2012)).

In this article, we study the relation between diversification of a financial institution's business activities on systemic risk. Our main motivation is that a common business mix across institutions does not necessarily imply a high correlation of exposures. A prime example is the insurance business: Since individual insurance contracts, for example in liability or automobile insurance, are loosely correlated across insurers, two insurers that exhibit the same business mix do not necessarily have a perfectly correlated exposure. Due to the stabilizing role of diversification, insurers with a more diversified business mix might then exhibit a lower contribution to systemic risk, i.e., a lower propensity to transmit economic shocks to other institutions.

As the financial crisis has shown, insurance companies are an integral as well as interconnected part of the financial sector. Their business activities provide essential services to the society, real economy, and financial markets by assuming, pricing, transferring, and diversifying risks (Thimann (2014)). The total size of the insurance market is notable: For example, total insurance premiums written in the United States have a volume of almost one tenth of total loans outstanding in the U.S.[1] U.S. insurance companies have 45% of the United State's GDP in assets under management (Bureau of Economic Analysis (bea) (2017)).[2]

When housing prices collapsed in 2008, the American International Group (AIG), one of the

[1]Based on Board of Governors of the Federal Reserve System (2017) and National Association of Insurance Commissioners (NAIC) (2017).

[2]The insurance sector has a similar size in other jurisdictions around the world. For instance, in the European Union, total loans outstanding are roughly 20 times larger than total insurance premiums (Insurance Europe (2016), European Banking Federation (2016)), and European insurers' assets under management comprise a volume of more than 60% of the EU's GDP (European Systemic Risk Board (2015)).

largest insurers in the United States, suffered investment losses of approximately 99 billion USD, whereof a substantial amount of 21 billion USD emerged from its securities lending activities (McDonald and Paulson (2015)). Since policymakers feared that a default of AIG might spill over to its counterparties and, thereby, amplify the financial crisis, AIG received a government bailout. The near-default of AIG has initiated a controversial debate about insurers' systemic risk contribution (e.g., Billio et al. (2012), Kessler (2013), Cummins and Weiss (2014), Thimann (2014)).

The case of AIG triggered two main hypotheses about the systemic risk of insurance activities: I) On the one hand, several authors argue that primarily non-core insurance activities[3], such as securities lending, but not core insurance activities, such as underwriting non-life or life insurance policies, contribute to systemic risk (e.g., The Geneva Association (2010), International Association of Insurance Supervisors (IAIS) (2011), Kessler (2013), Cummins and Weiss (2014)). II) On the other hand, several systemic risk measures suggest that life insurance companies contribute to a much larger extent to systemic risk than non-life insurers (e.g. Berdin and Sottocornola (2015), International Monetary Fund (2016), Kaserer and Klein (2017)).[4] An explanation that merges both hypotheses is that life insurance companies engage more in non-core insurance activities, and consequently, are contributing more to systemic risk than non-life insurers (Cummins and Weiss (2014)).[5] Additional explanations include that, due to their size, life insurers contribute more than non-life insurers to asset comovements by means of correlated sales of assets (Getmansky et al. (2017)) and exhibit higher leverage ratios (Harrington (2009), Bierth et al. (2015)). Thus, previous studies tend to focus on institutional differences between life and non-life insurers but do not provide a clear answer to the question whether and by what means core insurance activities contribute to systemic risk.

In this article, we develop a novel rationale for the effect of core insurance activities on systemic risk. Our main insight is that insurers with a more diversified business mix exhibit a lower contribution to systemic risk. We arrive at this conclusion in three steps: First, in Section 2 we document stylized facts about life and non-life insurance business cash flow. The main insight is

[3]Sometimes also referred to as *non-traditional non-insurance* (NTNI) activities.

[4]Systemic risk measures capture the risk that economic shocks spread across financial institutions and, potentially, lead to an impairment of financial markets, for instance ΔCoVaR by Adrian and Brunnermeier (2016) or Marginal Expected Shortfall by Acharya et al. (2017).

[5]For example, according to the Board of Governors of the Federal Reserve System (2017), in the first quarter of 2017 the average U.S. life (non-life) insurer engaged in loan activities by 1.1% (0.3%) and in security lending activities by 0.8% (0.4%) relative to total liabilities.

that cash flows arising from life insurance business are significantly less volatile and are slightly larger on average than that from non-life insurance business.

Second, in a simplified portfolio model in Section 3 we show that diversification across business activities can reduce financial contagion. For this purpose, we focus on credit risk as an exemplary channel for financial contagion that can potentially result in systemic risk (Benoit et al. (2017)). We study the impact of diversification across insurance activities on the expected loss of a counterparty that holds a financial claim to the insurer, e.g. resulting from subordinated debt or securities lending. By taking a portfolio perspective on the insurance holding's profit and loss, we find that the fraction of life business that typically minimizes the counterparty's credit risk is larger than 50%. This result stems from the stylized facts in Section 2, and is illustrated in Figure 1: If the insurance holding underwrites either more or less life business than at the credit-risk minimizing fraction (which equals 50% in this example), the counterparty's expected loss increases. The main driver of this result is a low correlation between life and non-life insurance activities. Furthermore, the credit-risk minimizing fraction of life business is increasing with an insurer's investment risk, and debt-to-equity ratio.

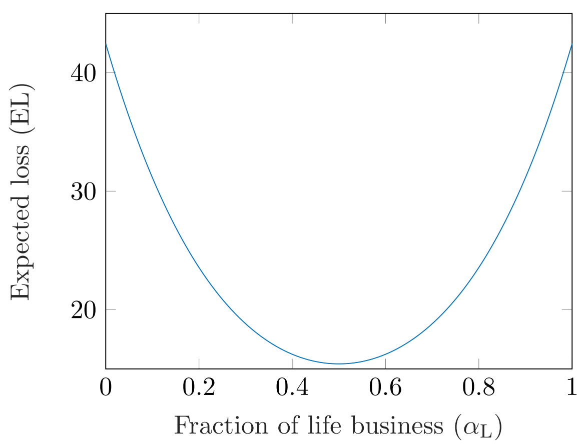


Figure 1: Sensitivity of the expected loss of a counterparty that holds a claim to an insurance holding with respect to changes in the fraction of life business α_L.

Third, in Section 4 we study empirical systemic risk measures and their relation to the business mix of 74 international insurance companies from 2007 to 2015. These measures are $\Delta\text{CoVaR}^{\leq}$, which is developed by Ergün and Girardi (2013) as an extension to ΔCoVaR from Adrian and Brunnermeier (2016), and the Average Expected Shortfall from Kubitza and Gründl (2017). Our main finding is that an average insurance holding with a fraction of slightly more than 50% of premiums written in life insurance exhibits the smallest contribution to systemic risk. Differences in the business mix are economically important: At the risk-minimizing fraction of life business, an increase or decrease by one standard deviation of the fraction of life business is related to an increase of 9% to 42% in an average insurer's contribution to systemic risk.

This result differs substantially from previous empirical studies about the systemic risk of insurers, as we do not categorize insurers into either life or non-life insurers, but employ the ratio of premiums written in life insurance to total premiums written as a proxy for the business mix. We emphasize that it is difficult, if not misleading, to categorize insurance holdings into life and non-life insurers, since many insurance holdings are multiliners that conduct both life and non-life insurance.[6] For example, the insurance group AXA, according to premiums written one of the largest insurers worldwide, is classified by its first SIC code (6311) as life insurer. However, during 2006 to 2014 it has on average underwritten only 65% of gross premiums in life insurance and 35% in non-life insurance. Thus, classifying AXA as life insurer leads to a profound misjudgment of AXA's business activities.[7] By studying an insurance holding's actual fraction of life business, we find that the systemic risk related to non-life insurance activities has been substantially understated in previous studies.

We also study the impact of active reinsurance business. We do not find a diversification effect between primary insurance and active reinsurance. This result is not surprising, since cash flows from these two activities are highly correlated. However, our empirical results suggest that an increase in the fraction of reinsurance business tends to increase the systemic risk-minimizing fraction of life business. This finding indicates that life insurance, characterized in particular by a low cash flow volatility, can partly compensate the negative effect of a relatively higher tail risk of reinsurance business. Nevertheless, we find that reinsurance as well as an insurer's debt-to-equity ratio or investment volatility have an insignificant effect on the diversification between life and non-life business. This result supports the view that diversification is primarily caused by a low degree of correlation between life and non-life cash flows.

Do our findings imply that all insurance companies should aim for full diversification in order

[6] Note that most popular systemic risk measures are based on financial market data and, thus, can be computed only for publicly listed insurance holdings but not for life or non-life (non-listed) subsidiaries.

[7] In contrast, the largest insurer according to total assets, Allianz Group, is classified as non-life insurer according to its first SIC code (6331), but has on average underwritten 35% of gross premiums in life insurance during 2006 to 2014.

to increase financial stability? Wagner (2010) argues that diversification across many financial institutions raises the homogeneity of their exposures. In his model, diversification increases the correlation of bank exposures, for example, by investing into the same assets. He shows that such correlated exposures increase the probability of joint failures and, thus, the likelihood of systemic crises. Therefore, there seems to exist an inevitable tension between an increase in an institution's stability and increase in the the likelihood of crises.

In Section 5 we argue that, however, diversification of insurance activities does not necessarily come with a larger correlation of exposures across insurers. While investment diversification might indeed result in all institutions holding the same portfolio, diversification across insurance activities does not imply common exposures across insurers. Instead, policyholders typically hold only a single insurance policy for one specific risk, for instance a car liability insurance.[8] Since typical insurance claims, e.g. from motor or homeowners' insurance, are independent across policies, exposures are loosely correlated across insurers. This argument, however, does not necessarily apply to catastrophic events like storms or earthquakes that simultaneously affect a large number of policyholders at different insurers. Nevertheless, since these events are usually reinsured and diversified geographically, it seems very likely that a stabilizing effect of diversification prevails.

We also find that multiline insurers exhibit smaller returns on assets and returns on equity than monoline insurers. Combined with our previous findings, this implies a trade off between economies of scope and economies of scale: The less diversified an insurer's business activities are, the more policies it underwrites in a particular line of insurance business. This increases benefits from *economies of scale with respect to risk taking* as insurers operate by exploiting the law of large numbers (Cummins (1974)). In contrast, economies of scope occur if an insurer diversifies across different insurance lines, which, for a given size of the insurer, decreases the number of contracts within each particular line. Since we find monoline insurers to have a higher profitability than multiliners, economies of scale seem to dominate economies of scope with respect to profitability. As we find the opposite effect with respect to systemic risk, insurance holdings might face high incentives to exploit economies of scale to increase profitability in contrast to exploiting economies of scope that could lower their contribution to systemic risk.

[8] In property and casualty insurance, in particular, insurers typically prohibit insuring the same risk with a second insurer.

Our analysis builds on previous work on the relation between financial institutions' business activities and financial crises. Allen and Carletti (2006) and Allen and Gale (2007) show that credit risk transfer from banks to insurers can cause insurer-specific economic shocks to spill over to the banking sector due to an asset liquidation channel since insurers and banks are exposed to the same assets. Similarly, in the models of Wagner (2008) and Wagner (2010), diversification of banking activities causes them to hold the same assets. Thus, if all banks in a system were fully diversified, they would either default together or no bank defaults. In this case, diversification increases the likelihood of systemic crises as it makes banks more homogeneous. Battiston et al. (2012) show that a high level of risk diversification can make financial networks less resilient, and Goldstein and Pauzner (2004) find that portfolio diversification by investors can lead to contagion across countries. From an empirical perspective, Brunnermeier et al. (2012) find that non-interest income of banks increases their contribution to systemic risk, while Köhler (2015) finds that non-interest income increases the stability of saving and cooperative banks.

We contribute to this literature in two ways: First, we extend previous studies on diversification by providing empirical evidence for the relation between the diversification of business activities and systemic risk. Second, we do not consider diversification in terms of asset investments but in terms of business activities. The important distinction is that institutions, particularly insurers, are able to diversify across business activities without necessarily increasing common exposures. This is one explanation of our finding of a beneficial impact of diversification for systemic risk that differs from the theoretical predictions of Wagner (2008) and Wagner (2010).

Another strain of literature related to our article comprises empirical studies on the effect of diversification on the profitability and firm value of financial institutions. For example, Stiroh and Rumble (2006), Stiroh (2006) and Laeven and Levine (2007) find that diversification of business activities at banks and U.S. financial holding companies does not have a beneficial but rather negative effect on performance and market value. In contrast, the results of Elsas et al. (2010) suggest that diversification increases bank profitability, which they argue is mostly due to the use of more granular measures of profitability. Our study differs along two dimensions from the previous studies: First, we examine insurance holdings in contrast to banks. Importantly, due to the low correlation across different insurance activities as well as between insurance and investment activities, the diversification benefit for insurers is potentially larger than for banks. Second, our focus is on financial contagion in contrast to profitability. Since financial contagion is clearly driven by other determinants than profitability, such as interconnectedness, joint exposures, or volatility, we expect different results. Nevertheless, we directly contribute to this literature, as well, by providing empirical evidence that, on average, multiline insurers exhibit a smaller return on assets than monoline insurers which is consistent with previous studies that find business diversification to decrease the profitability of banks.

Finally, we extend previous empirical studies on the determinants of insurance companies' contribution to systemic risk. We differ from these studies in three important ways: First, we allow for a diversification effect between different business activities, while most other studies categorize insurers into non-life and life insurers and find that systemic risk is larger at life insurers (Weiß and Mühlnickel (2014), Bierth et al. (2015), Kaserer and Klein (2017)). Berdin and Sottocornola (2015) conduct panel regressions with a linear effect of life insurance on systemic risk and find it to be positive. We contrast these studies by finding a significant non-linear effect of life insurance on systemic risk. Second, we distinguish between systemic risk towards the financial system and towards the real economy. This seems important, as systemic risk might involve different systems of institutions, and contagion within the financial system does not necessarily affect the real economy. Third, we differentiate between measures for short-term and long-term systemic risk. As Kubitza and Gründl (2017) show, systemic spillovers can take a long time to resolve, particularly during crises. Thus, measures for the short-term contribution to systemic risk might underestimate the actual risk contribution of financial institutions. To account for this underestimation, we employ the Average Excess CoSP from Kubitza and Gründl (2017).

2 Stylized Facts about Life and Non-Life Insurance

In the following, we distinguish between insurance and investment activities of insurance companies. First, we focus on insurance activities: Claims and the growth in insurance reserves in life insurance are usually more predictable than that in non-life insurance (Insurance Europe (2014)). For example, annuity payments or death benefit payments are fixed upon the purchase of contracts. In contrast, indemnity payments in non-life insurance substantially vary due to ex ante uncertain loss severities and catastrophic events. Thus, non-life cash flow distributions can exhibit substantial tails and a larger volatility than cash flows in life insurance (Cummins and Weiss (2016)).

The typical duration of non-life contracts is one year. Thereafter, premiums can be altered by insurers, and policyholders have the chance to change insurers or insurance coverage. In contrast, a life insurer cannot change premiums, death benefit, or annuity payments of previously sold contracts. The typically very long contract duration of life insurance contracts of more than 10 years (European Insurance and Occupational Pensions Authority (EIOPA) (2014)) implies a very stable premium income to life insurers' cash flows. In contrast, that of non-life insurers' is potentially more volatile as it is more exposed to changes in the demand for insurance.

We underpin these stylized facts by empirical evidence employing the ratio of U.S. insurance holdings' annual underwriting profit (and loss) to net premiums earned. In Table 1 we report the mean and the volatility of this ratio for the life & health (L&H) as well as property & casualty (P&C) insurance business of these companies. The data is based on observations from 2006 and 2016 as provided by A.M. Best Company. In line with the previous arguments, the volatility of the (relative) underwriting gain is substantially larger for property & casualty (P&C) insurance than for life & health (L&H) insurance.[9] Similarly, several empirical studies find life insurers' return on assets and return on equity as well as the growth rate in direct premiums and reserve flows to be very stable over time (for example Cummins (1973), Adams (1996), and Greene and Segal (2004)).

Another stunning finding is that the average underwriting profit is negative in both lines.[10] In fact, 30% (46%) of insurer-year observations in our sample exhibit an underwriting loss in P&C (L&H) business. This is in line with the findings of Kahane and Nye (1975) for the U.S. P&C insurance industry. Consequently, insurance holdings substantially rely on other sources of income, such as investment profits, to finance losses.

Second, we study the investment behavior of insurers. To mitigate liquidity risk, insurance companies' asset investment behavior is typically driven by the characteristics of their liabilities. Table 2 depicts U.S. L& and P&C insurers' investment portfolio for exemplary asset classes. In 2016, an average U.S. life insurer held roughly 72% of total financial assets in bonds, while it was 55% for an average non-life insurer. The massive bond portfolios of life insurers typically consist of long-term

[9]According to a F-test, the difference between the mean underwriting gain in P&C and L&H insurance is statistically significant at the 1% level.

[10]According to a T-test, the difference in the volatility of the underwriting gain in P&C and L&H insurance is not statistically significant.

	Life & Health	Property & Casualty
Mean Underwriting Gain	-0.27	-0.21
Volatility of Underwriting Gain	2.17	4.09

Table 1: Underwriting gain relative to premiums earned: Mean and volatility (standard deviation).
The sample consists of 1165 (707) insurer-year observations for the underwriting gain and premiums earned in property & casualty (life & health) insurance business of 146 U.S. insurance holdings during 2006 to 2016. Source: *A.M. Best Company, Own calculations.*

bonds that are held to maturity in order to reduce the duration gap between assets and liabilities (Thimann (2014)).[11] Thus, cash flows from insurers' bond investments are relatively stable over time. Moreover, Table 2 shows that L&H insurers tend to invest more heavily in precautionary but illiquid non-financial assets that yield stable cash flows (e.g., mortgages or loans). In contrast, P&C insurers exhibit larger investments in speculative and liquid financial assets (e.g. equity). A similar investment behavior can be observed in other countries. For example, in 2016 an average German L&H (P&C) primary insurer held 86% (75%) of financial assets in bonds and debentures, 24% (18%) in loans and mortgages, and 4% (7%) in stocks (German Insurance Association (GDV) (2017)).[12]

Asset Class	Life & Health	Property & Casualty
Bonds	72.2%	54.8%
Mortgages	11.0%	0.9%
Contract Loans	3.2%	0%
Common and Preferred Stock	4.2%	29.6%

Table 2: U.S. total life & health and property & casualty insurance industry's investment portfolio breakdown into exemplary asset classes in percentages according to the National Association of Insurance Commissioners (NAIC) (2016) at year-end 2016.

Finally, we examine the overall free cash flow resulting from life and non-life insurance business. For this purpose, we examine the return on equity of 74 international insurance holdings. The data sample is described in more detail in Section 4.3. First, we find that the return on equity of insurance holdings with a ratio of more than 99% in premiums written in life insurance exhibits

[11] The German Insurance Association (GDV) reports an average duration of German life insurers' assets of 8.2 years and of German life insurer's liabilities of 14.8 in 2013.

[12] The German insurance market includes several large international insurance companies, for example the Munich Re group or Allianz. The total size of German insurers' assets is more than one quarter of that of U.S. insurers (German Insurance Association (GDV) (2017), National Association of Insurance Commissioners (NAIC) (2016)).

a significantly smaller volatility (0.069) than that with a ratio of more than 99% written non-life insurance (0.085).[13] This finding is in line with the previous arguments suggesting that life insurance cash flows exhibit a smaller volatility.

Second, we examine differences in the average return on equity. By controlling for year-fixed effects, an insurer's (log) total assets, leverage, and market-to-book ratio, we find that the return on equity is typically larger for insurance holdings with a larger share of life business (as measured by the proportion of premiums written in life insurance).[14] The results are presented in Table 24 in Section B.3. Overall, the previous empirical evidence suggests that cash flows are significantly more volatile and tend to be larger on average in life insurance business compared to non-life insurance business.

3 Business Mix and Counterparty Credit Risk

In the following, we examine the impact of an insurance holding's business mix on counterparty credit risk. As a (partial) default of the insurance holding negatively affects the counterparty, counterparty risk is one potential channel for the transmission of economic shocks, i.e., financial contagion. This channel exists, for example, if an insurance holding has issued subordinated debt to a counterparty:[15] If the insurance holding's free cash flow (after covering policyholder claims) is not sufficient to repay the debt, the shock that originally only affected the insurer spills over to the debt holder by endangering its financial health, as well. The same rationale holds for other financial linkages, e.g., stemming from derivatives trading or securities lending.[16]

The model is based on a portfolio view on an insurance holding that has the opportunity to invest in one life and one non-life insurance company. This set-up is analogous to the one employed by Kahane and Nye (1975) to examine the efficiency of insurance underwriting portfolios. More recently, Stiroh (2006) uses the same framework to study diversification between interest and non-

[13] According to a F-test, the difference between the volatilities is significant at the 5% level.

[14] Without accounting for control variables, a T-test of the return on equity for insurance holdings with a large and small share of life business turns out to be insignificant.

[15] Based on data from *A.M. Best Company*, we find that, during the years 2006 to 2016, 90.2% of all U.S. insurance holding companies have issued debt or debt-like instruments (such as surplus notes). These amount on average to 10.4% of an average insurance holding's total liabilities.

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

interest income of banks.

3.1 Model

At time $t = 0$, the insurance holding is equipped with an initial amount of equity capital E and one liability position in form of a claim of size D that is due at time $t = 1$ to a counterparty. Without loss of generality, the holding's total funds are scaled to one unit, $L = E + V_0(D) = 1$, where $V_0(D)$ is the value of the counterparty claim at time $t = 0$. Total funds are invested at time $t = 0$ into life and non-life insurance operating companies that sell life and non-life insurance contracts, respectively.[17] The holding invests the amount $\alpha_L \in [0, 1]$ in the life and the residual amount in the non-life operating company. As it is typical in practice, we assume that, upon the investment, the holding owns the major share of both operating companies, such that these are consolidated at the holding level.[18] We call the operating companies *subsidiaries* from here on.

The subsidiaries engage in selling insurance contracts at time $t = 0$. This results in cash flows at time $t = 1$ covering claim payments to policyholders, premium inflow from newly sold or multiple-premium (long-term) contracts[19], investment profits, and the growth of insurance reserves for old and new contracts. Eventually, the insurance holding's investment generates the returns R_L and R_{NL} stemming from the subsidiaries' profits, where R_L and R_{NL} denote the subsidiaries' returns on equity.

The free cash flow of the insurance holding is then given by

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

For simplicity, we assume that returns are normally distributed.[20]

[17]For simplicity, we assume that the holding's investment decision does not affect the business activities of the operating companies. Hence, it does not affect the subsidiaries' existing capital structures.

[18]Most insurance holdings own the major share of their operating companies. For example, almost all subsidiaries of AXA (`https://www.axa.com/en/investor/organization-charts`) or Allianz (`https://www.allianz.com/en/about_us/who_we_are/company-structure-holdings/`) are fully owned by the respective holding company.

[19]For example, term life insurance policies involve a periodic (typically annual or monthly) premium paid by policyholders and one death benefit claim paid by the insurer if the policyholder deceases, while annuities involve periodical (claim) payments of a previously fixed amount as along as the annuitant is alive. In contrast, non-life contracts typically comprise only one premium payment at the beginning of the contract and an indemnity payment only in case a random claim event occurs during the contract's lifetime.

[20]It can be justified, for example, by the central limit theorem if the subsidiaries' cash flows are well-diversified. As our results are mainly driven by the effect of diversification on volatility, we do not expect the particular distribution of cash flows to have a large effect on our main results.

The insurance holding is obligated to serve the claim D to a counterparty at time $t = 1$. For instance, D might be the repayment of debt. The repayment of the claim is endangered in case the holding's free cash flow (resulting from the subsidiaries' returns) is small. This situation can occur particularly upon an economic shock to the subsidiaries' cash flows. A prominent example is the situation of AIG during the 2007-08 financial crisis: As AIG faced substantial asset investment losses, it was not able to serve all collateral calls made by counterparties in its security lending transactions (McDonald and Paulson (2015)).[21]

If the subsidiaries' returns are sufficiently large, the holding's free cash flow covers the counterparty's claim. Otherwise, the holding company might (partially) default.[22] We measure the level of counterparty credit risk by the expected loss that the counterparty faces in its transaction with the insurance holding, which is given by

$$EL = D - \mathbb{E}\left[\min\left(D, R\right)\right] = (D-\mu)\Phi\left(\frac{D-\mu}{\sigma}\right) + \sigma\varphi\left(\frac{D-\mu}{\sigma}\right), \tag{2}$$

where Φ is the cumulative distribution function and φ the probability density function of a standard normal distribution, and μ and σ^2 are the expectation and variance of the insurance holding's free cash flow R at time $t = 1$.

EL reflects the value of an European put option at strike D on the holding's free cash flow R: If the latter is large enough, the loss is zero, and vice versa. From option pricing theory it is well-known, that the price of a European put option is increasing with the underlying's volatility.[23] Here, the underlying is the cash flow with volatility

$$\sigma^2 = \alpha_L^2\sigma_L^2 + (1-\alpha_L)^2\sigma_{NL}^2 + 2\alpha_L(1-\alpha_L)\sigma_L\sigma_{NL}\rho, \tag{3}$$

where ρ is the correlation between life and non-life subsidiaries' returns. The investment cash flows are likely to be positively correlated particularly as investments might overlap or exhibit a positive

[21] As in the case of AIG, the counterparty claim in our model might as well result from a transaction undertaken by one of the subsidiaries that has taken place in an intermediary period $t = \tau \in (0,1)$ after the holding's investment decision, where the amount D of the counterparty claim is guaranteed by the insurance holding and R_L and R_{NL} are the returns before the full counterparty claim is paid by the subsidiary.

[22] However, we assume that the subsidiaries exhibit a very low individual probability of default such that $\mathbb{P}(R_L < -1) = \mathbb{P}(R_{NL} < -1) \approx 0$ is negligible. Then, our results hold in case the holding company has limited or unlimited liability towards the subsidiaries.

[23] This follows from a positive vega of European put options (Hull (2003)).

market beta. In contrast, claims in life and non-life business (e.g. death benefits in term life and indemnity payments in homeowners' multiple peril insurance) typically exhibit a very small correlation. Hence, we suppose that $0 < \rho < 1$. The following lemma reveals that diversification between life and non-life business reduces credit risk if the correlation ρ is sufficiently small. This implies that, everything else being equal, a multiline insurance company exhibits a smaller credit risk than either a life or non-life monoline insurer. Moreover, the lemma shows that an increase in the life (non-life) return volatility decreases (increases) the credit-risk minimizing fraction of life business.

Lemma 1. *If the expected returns from life and non-life business do not differ, the credit-risk minimizing fraction of life business is given as*

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

It is $\alpha_L^* \in (0,1)$ *if* $\rho < \min\left(\frac{\sigma_{NL}}{\sigma_L}, \frac{\sigma_L}{\sigma_{NL}}\right)$. α_L^* *is decreasing (increasing) with the return volatility of life (non-life) business, if* ρ *is sufficiently small.*

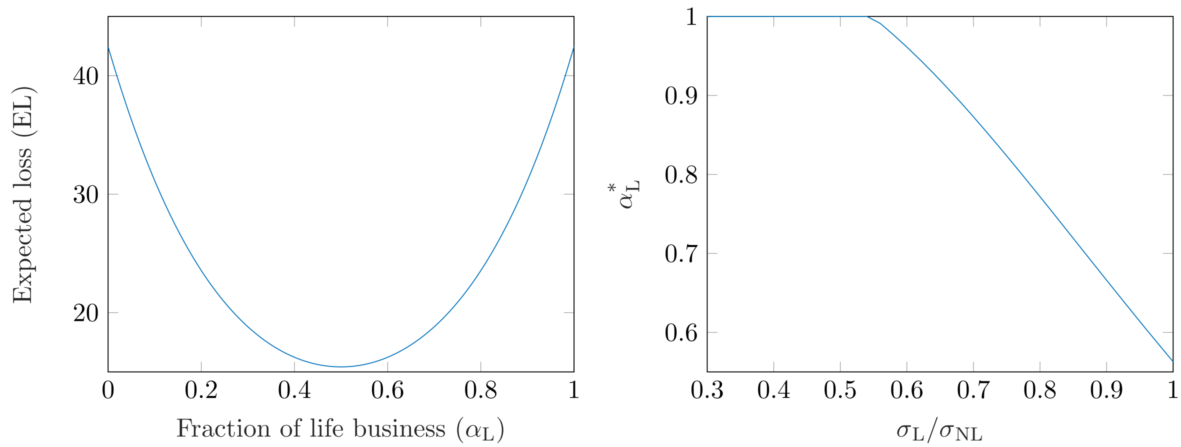
If $\rho > 0$ *and* $\sigma_L < \sigma_{NL}$*, it is* $\alpha_L^* > 0.5$. *Proof: See Appendix A.*

Figure 2 illustrates the results from Lemma 1. First, Figure 2 (a) shows that the expected loss is u-shaped in the fraction of life business. This implies the existence of a minimum, namely that an insurance holding with the fraction of life business α_L^* exhibits the smallest credit risk. A deviation from α_L^* relates to a larger credit risk since then shocks from one business activity are diversified less efficiently. As we assume the same expected returns from life and non-life business in Lemma 1, α_L^* achieves a minimum variance portfolio of the holding company.

Second, Figure 2 (b) depicts α_L^* with respect to the volatility of the life and non-life companies' returns. Intuitively, the more volatile the return from life business is relative to that from non-life business, the smaller is the diversification benefit of underwriting more life business. Consequently, holding companies with a smaller fraction of life business exhibit the smallest credit risk.[24]

Since we show in Section 2 that life insurance business is related to a smaller volatility than non-life insurance business, Lemma 1 implies that credit risk is minimal for an insurance holding

[24] Note that Lemma 1 implies that this relationship only holds in case $\rho < \sigma_L/\sigma_{NL}$.



(a) $\sigma_L = \sigma_{NL}$.

(b) $\sigma_L \leq \sigma_{NL}$.

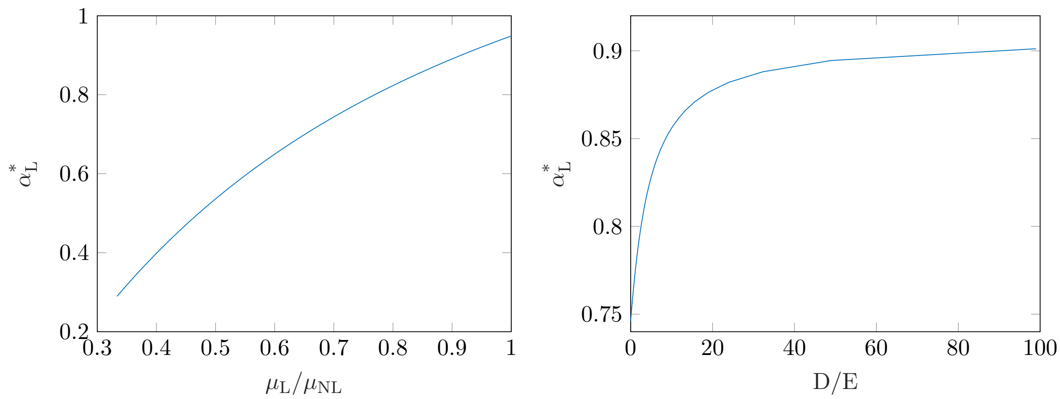
Figure 2: Fraction of life business α_L^* that minimizes credit risk for the following cash flow characteristics: Expected free cash flow $\mu_L = \mu_{NL} = 1$, non-life cash flow volatility $\sigma_{NL} = 0.5$, life and non-life cash flow correlation $\rho = 0.5$, claim $D = 0.5$, and equity capital $E = 1$.

with more than 50% of funds invested in life insurance business. This finding is consistent with Figure 2 (b).

Section 2 also suggests that the expected return on equity is larger in life insurance than non-life insurance business. Figure 3 (a) depicts the credit-risk minimizing fraction of life business α_L^* with respect to the expected return from life business (μ_L) relative to that from non-life business (μ_{NL}). Intuitively, a larger expected life return increases the diversification benefit of life business and, thus, α_L^* is increasing with μ_L/μ_{NL}.

If expected returns from life and non-life business differ, the relation between equity capital E and the claim D is an important determinant of α_L^*. The larger the claim D relative to the holding's equity capital, the less likely is the repayment of the counterparty's claim. Instead, the counterparty is more likely to receive the holding's remaining free cash flow. If the expected return from life business is larger than from non-life business, it is beneficial to underwrite more life business the less equity capital the holding owns for a given claim size D, as Lemma 2 shows. Figure 3 (b) illustrates this finding: The larger the insurance holding's claim-to-equity ratio D/E, the larger is the fraction of life business that minimizes credit risk.

Lemma 2. *Assume that the return from life business is less volatile and larger in expectation than that from non-life business. If the debt-to-equity ratio is sufficiently large, it is* $\alpha_L^* = 1$.



(a) Differences in Expected Returns.

(b) Debt-to-Equity Ratio.

Figure 3: Fraction of life business α_L^* that minimizes credit risk. The baseline return characteristics are: expected life and non-life free cash flow $\mu_L = 1$ and $\mu_{NL} = 1$, life return volatility $\sigma_L = 0.4$, non-life return volatility $\sigma_{NL} = 0.5$, life and non-life return correlation $\rho = 0.5$, $D = 0.5$, and equity capital $E = 0.5$.

Proof: See Appendix A.

Finally, we consider the impact of changes in the investment return volatility. We are particularly interested in an increase in investment return volatility. This might relate to higher systematic risk during crises times or to a larger share of risky assets in the subsidiaries' asset portfolios.[25] For this purpose, we split up the subsidiaries' returns into that from insurance and investment activities, $R_L = 1 + R_{INS,L} + R_{INV,L}$ and $R_{NL} = 1 + R_{INS,NL} + R_{INV,NL}$, where $R_{INS,x}$ and $R_{INV,x}$ are the rates of return from insurance and investment activities for subsidiary $x \in \{L, NL\}$. We assume that the subsidiaries' investment return comprises an idiosyncratic component z_{INV} and systematic component m_{INV}, such that $R_{INV,x} = z_{INV,x} + m_{INV}$, with $x \in \{L, NL\}$, and $z_{INV,x}$ and m_{INV} being pairwise independent and normally distributed. The holding's free cash flow is then given as $R = 1 + \alpha_L R_{INS,L} + (1 - \alpha_L) R_{INS,NL} + \alpha_L z_{INV,L} + (1 - \alpha_L) z_{INV,NL} + m_{INV}$.

Suppose now that the systematic volatility $\sigma_m = \sigma(m_{INV})$ increases. Figure 4 shows that in this case α_L^* increases, as well.[26] The intuition is similar to that underlying the interaction with the debt-to-equity ratio: The less likely the repayment of the full counterparty claim, the more

[25] For example, Becker and Ivashina (2015) document that insurance companies search for yield in the sense of choosing the most risky assets within one NAIC risk class.

[26] This result is robust to other initial parameter specifications that are consistent with our findings from Section 2.

beneficial is a larger expected return that is achieved by investing in life business. This finding is consistent with a *flight to safety*-behavior.

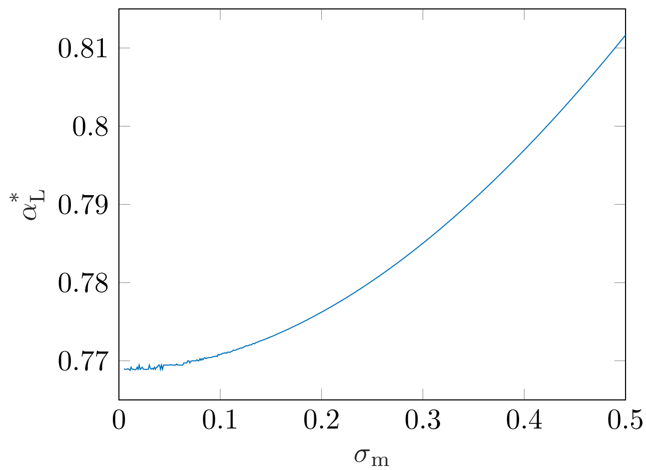


Figure 4: Fraction of life business α^*_L that minimizes credit risk for different levels of systematic risk. The baseline return characteristics are: expected insurance activities' rate of return $\mu_{INS,L} = 0.2$ and $\mu_{INS,NL} = 0.1$, rate of return volatility $\sigma_{INS,L} = 0.1$ and $\sigma_{INS,NL} = 0.15$, expected market rate of return $\mu_m = 0$, idiosyncratic expected rate of return $\mu_{z,L} = 0.1$ and $\mu_{z,NL} = 0.15$ and volatility $\sigma_{z,L} = 0.1$ and $\sigma_{z,NL} = 0.2$, claim $D = 0.5$, and equity capital $E = 0.5$. We assume independence between all rates of return.

3.2 Hypotheses

In our theoretical model, we study counterparty credit risk as one exemplary channel for the transmission of economic shocks. In the following, we transfer the results of our model into hypotheses about the relation between systemic risk and business activities.

(H1): Diversified insurers have a smaller contribution to systemic risk than non-diversified insurers.

(H2): Insurance holdings with the smallest contribution to systemic risk underwrite more than 50% of their business in life insurance.

(H3): The more volatile an insurance holding's investment activities, the larger is the systemic risk-minimizing fraction of life business.

(H4): The larger an insurance holding's debt-to-equity ratio, the larger is the systemic risk-minimizing fraction of life business.

Moreover, from our model we can also derive an intuition about the relation between systemic risk and active reinsurance business. First, we expect primary insurance and reinsurance liabilities to be positively correlated, particularly since insurers can reinsure risks by themselves[27] and catastrophes are likely to hit both primary insurance and reinsurance claims. Therefore, we expect the diversification effect between primary insurance and active reinsurance to be much smaller than between life and non-life insurance:

(H5): Systemic risk stemming from reinsurance cannot be diversified by primary insurance, and vice versa.

Second, reinsurers have the opportunity to draw up contracts on an individual basis, which might limit their exposure to risk (European Commission (2002)). Moreover, they typically have the possibility to invest in projects that require a high investment volume and yield stable cash flows (e.g., infrastructure investments). Thus, active reinsurance can be more stable than non-life business. However, it is also subject to a potentially larger tail risk, resulting particularly from non-proportional reinsurance contracts that expose them to losses from catastrophes (European Commission (2002)). Thus, on the one hand, a higher degree of investment diversification and individual contracts might reduce volatility, on the other hand, tail risk might increase volatility. Anecdotal evidence from the reinsurance industry suggests that the impact of tail risk prevails and, thus, similar to hypothesis ($H3$), we expect the diversification benefit of life business to increase with reinsurance business:

(H6): The higher an insurance holding's fraction of active reinsurance business, the larger is the systemic risk-minimizing fraction of life business.

4 Empirical Analysis of Systemic Risk

4.1 Systemic Risk Measures

We focus on systemic risk measures for the contribution of an institution to the risk of a system of institutions. The idea of these measures is to interpret an extremely large negative market equity return as signal for an economic shock. Conditionally on an economic shock to one institution, the measures capture the risk that the shock is transmitted to other institutions. If shocks are sufficiently large, they might cascade through the entire system of institutions, and eventually

[27] This is achieved by setting up an affiliated reinsurer. This mechanism is referred to as *shadow insurance* by Koijen and Yogo (2016).

result in the realization of systemic risks.

We identify shocks based on the total return index (r^I) of each institution I as this index incorporates dividend payments. To capture wide-spread shocks to a system of institutions, we compute a (market-)value-weighted index (r^S) of total return indices for institutions within this system. For constructing the system's index, we follow the methodology of Kubitza and Gründl (2017) and exclude the currently considered insurance company from the index in order to mitigate endogeneity in our results.[28]

An institution's dependence-consistent $\Delta\text{CoVaR}^{\leq}$ approximates its short-term (i.e. contemporaneous) contribution to a system's tail risk. It has been suggested by Ergün and Girardi (2013) and Mainik and Schaanning (2014), and is defined as

$$\Delta\text{CoVaR}^{\leq}_{S|I}(q) = \text{CoVaR}_{r^I \leq VaR^I(q)}(q) - \text{CoVaR}_{\mu^I - \sigma^I \leq r^I \leq \mu^I + \sigma^I}(q) \tag{5}$$

where μ^I and σ^I are the mean and standard deviation of institution I's total return distribution, respectively, and q denotes the confidence level, i.e. the severity of shocks. The system's Value-at-Risk conditional on institution I being in distress, $\text{CoVaR}_{S|I}$, is defined as the q-quantile of the system's conditional return distribution

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

where r^S is the system index' return. Hence, the dependence-consistent $\Delta\text{CoVaR}^{\leq}_{S|I}$ reflects the change in the system's tail risk if institution I is in distress (i.e. if it shows a tail return). Thereby, the institution's contribution to systemic risk is measured as the difference in the system's risk conditional on the institution being in distress and conditional on the institution's benchmark state specified by one standard deviation around its mean return.

ΔCoVaR is based on the system's Value-at-Risk conditional on the institution being exactly at its Value-at-Risk, $\text{CoVaR}_{r^I = VaR^I(q)}$. In contrast, the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ also takes an institution's distress beyond its Value-at-Risk into account. Mainik and Schaanning (2014) show that, due to this property, the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ is continuously increasing

[28] Otherwise, the index returns, r^S, and institution's returns, r^I, are correlated by construction already. In Appendix B.1 we briefly review the methodology of index construction.

in the level of dependence between the system's and institution's return, which seems a desirable property to measure risk but is not fulfilled by ΔCoVaR. Since $\Delta\text{CoVaR}^{\leq}$ is inversely related to an institution's contribution to systemic risk, we use $-\Delta\text{CoVaR}^{\leq}$ in the panel regressions, such that a higher value relates to higher risk.

Adrian and Brunnermeier (2016) show that $\Delta\text{CoVaR}= -\rho^{I,S}\sigma^{I}\Phi^{-1}(q)$ if total returns follow a bivariate normal distribution, where $\rho^{I,S}$ is the correlation between the institution's and system's returns and σ^{I} the standard deviation of the institution's return. Thus, in accordance with the previous section, systemic risk is minimized with respect to ΔCoVaR if the volatility of the institution's total return is minimized for a given level of correlation. Although in practice equity returns are typically not normally distributed, this observation suggests that empirical systemic risk measures capture volatility in a similar way to the expected credit risk exposure in Section 3. Thus, we expect a similar effect of diversification.

Kubitza and Gründl (2017) find that an institution's distress can have a persistent contagious impact on the financial and non-financial system, particularly in times of crises. Their results suggest that a high uncertainty and slow information processing during crises leads shocks of one institution to have a long-term impact of up to 1 month on other institutions. Measures for contemporaneous systemic risk, such as the $\Delta\text{CoVaR}^{\leq}$, do not capture this long-term effect as they are based on instantaneous correlation. Therefore, Kubitza and Gründl (2017) suggest to aggregate the contribution to systemic risk over time. Their measure is based on the Conditional Shortfall Probability (CoSP) as given by the likelihood of a shock in the system (i.e. the system's return being in its tail) τ days after an institution's distress (i.e. the institution's return being in its tail),

$$\psi_{\tau}^{S|I} = \mathbb{P}\left(r_{\tau}^{S} \leq VaR^{S}(q) \mid r_{0}^{I} \leq VaR^{I}(q)\right). \tag{7}$$

CoSP also captures potential feedback loops and cascading effects that might occur if the institution's shock is circulating through the system. This property seems desirable from a regulator's perspective, as it captures the total impact of systemic spillovers. Nonetheless, over time the institution shock's impact on the system vanishes. The aggregation of the CoSP over a given time period yields the institution's Average Excess CoSP,

$$\overline{\psi}_{S|I} = \frac{1}{\tau_{\max}} \int_0^{\tau_{\max}} (\psi_\tau - q) d\tau, \tag{8}$$

which is the average excess shortfall probability of a system conditional on a previous shock to a specific institution. We employ $\overline{\psi}_{S|I}$ as a second measure and interpret it as an institution's long-term contribution to systemic risk. As suggested by Kubitza and Gründl (2017), we set the maximum considered time lag to $\tau_{\max} = 100$ days.

Both the ΔCoVaR$^{\leq}$ and Average Excess CoSP assess the risk that a shock spreads from one institution to a system of institutions without specifying the transmission channel. A prime example for such a transmission channel is counterparty credit risk as studied in the previous section: If an institution A issues subordinated debt in the form of a bond that is purchased by institution B, B is exposed to the counterparty credit risk of A. If A faces an economic shock, this shock might impair the ability of A to repay the debt to B. If such a channel exists and equity markets are weakly informationally efficient, equity prices of institution B will react to the economic shock of A to the extent that the counterparty credit risk increases. In this case, measures such as ΔCoVaR$^{\leq}$ or the Average Excess CoSP will reflect the systemic risk contribution of institution A.

There exist several other systemic risk measures, from which the most popular are SRISK by Acharya et al. (2012) and the marginal expected shortfall (MES) by Acharya et al. (2017). These measures capture the tail risk of an institution during a system's distress. Hence, they are based on a direction of contagion inversely related to ΔCoVaR$^{\leq}$ and Average Excess CoSP, namely from a system to an institution.

For all measures we employ a confidence level of $q = 5\%$, i.e. an institution's and system's return below the 5%-quantile of the corresponding return distribution is interpreted as an economic shock. The computation is based on 7-year rolling windows such that the value of a measure at the end of a given year t is based on observation from years $t-6, ..., t-1, t$. For ΔCoVaR$^{\leq}$ we employ Maximum-Likelihood estimates and a Generalized Linear Model for $\overline{\psi}$ analogously to Kubitza and Gründl (2017).

4.2 Explanatory Variables

Our main variable of interest is the fraction of life business within an insurance holding. The theoretical model is based on the diversification of cash flows related to insurance business. As insurance premiums are part of an insurer's cash flow, we approximate the fraction of life business by gross premiums written in life business relative total gross premiums (*Life*). Similarly, the fraction of gross reinsurance premiums relative to total gross premiums written serves as a proxy for an insurer's engagement in active reinsurance business (*Reinsurance*).

We control for several other firm characteristics. Non-core activities might involve more risky and interconnected financial transactions of insurers and, thus, might contribute to systemic risk. Analogously to Bierth et al. (2015) we approximate non-core activities by the fraction of total liabilities over insurance reserves at the holding level. We proxy an insurer's size by the natural logarithm of its total assets. Previous studies find that an institution's size is significantly related to its systemic risk (e.g., Weiß and Mühlnickel (2014)). The intuition is that large institutions are more likely to be too-big-to-fail as well as too-complex-to-fail than small institutions (International Association of Insurance Supervisors (IAIS) (2016)) as the default of a large insurer could result in large externalities in form of directly imposed losses. Large insurers also tend to hold and sell common assets which implies a larger likelihood of correlated fire sales that may deteriorate asset prices (Getmansky et al. (2017)).

We control for an insurer's market-to-book ratio and return on equity (RoE) to proxy for an insurer's expected and past performance and profitability, respectively.[29] A high profitability might serve as protection against economic shocks, since it typically increases an institution's solvency margin (de Haan and Kakes (2010)). Following this argument, the market-to-book ratio and return on equity might increase an insurer's resilience towards shocks and thus be negatively related to its contribution to systemic risk. However, since high returns and growth expectations might also coincide with higher operational and investment risks (Milidonis and Stathopoulos (2011)), market-to-book and return on equity could also be positively related to an insurance company's contribution to systemic risk. Hence, it is not surprising that similar studies find an ambiguous effect of these variables on systemic risk (e.g., Weiß and Mühlnickel (2014) and Bierth et al. (2015)).

[29] The market-to-book ratio is defined as the market value of common equity divided by the book value of common equity.

Another important explanatory variable is an insurer's leverage ratio. By following Fahlenbrach et al. (2012) and Acharya et al. (2017), we approximate an insurer's leverage as the book value of assets minus book value of equity plus market value of equity, divided by the market value of equity. The empirical evidence on the relation of an insurance company's leverage to systemic risk is mixed. In general, leverage in insurance is substantially different to that of banks since insurance reserves are the largest part of an insurer's liabilities (Thimann (2014)). Since policyholders' liabilities are typically pre-funded (i.e., before claims are made) and incorporate a safety margin, an insurer's leverage might not necessarily increase its contribution to systemic risk. Indeed, for a given size of premiums, a high leverage ratio could signal high insurance reserves and, thus, a high buffer for future insurance losses. However, unconditionally, a high leverage ratio might also relate to a high ratio of insurance risk to equity and, thus, might reduce an insurer's ability to absorb losses, e.g. from catastrophes or large asset losses. This view is supported by Harrington (2009), Chen et al. (2013), Berdin and Sottocornola (2015), and Bierth et al. (2015) who find that more highly levered life insurance companies tend to contribute more to systemic risk.

To approximate investment volatility, we calculate the fraction of total equity stock investments relative to an insurer's total investments. As this investment class is among the most volatile investments of insurers, we expect the investment return's volatility to increase with a larger fraction of stock investments (*Stocks*). Finally, we account for changes in the regulatory or market environment by including year fixed effects. Standard errors are clustered by insurers to account for autocorrelation of the variables.

4.3 Data

To compute the systemic risk measures we rely on daily total return indices provided by *Thomson Reuters Financial Datastream*. We include all insurers that were alive in 2016, or dead in 2016 but listed in the considered estimation window in one of the five largest global markets (United States, Germany, United Kingdom, China, and Japan).[30] To compute shocks to the global financial system, we consider an index comprised of all financial institutions from Datastream that exhibit at least 1500 return observations from 2007 to 2015. In Appendix B.1 we describe the construction and composition of the global financial system index (FIN). The total number and type of institutions

[30]We choose this restriction to narrow down the resulting amount of data.

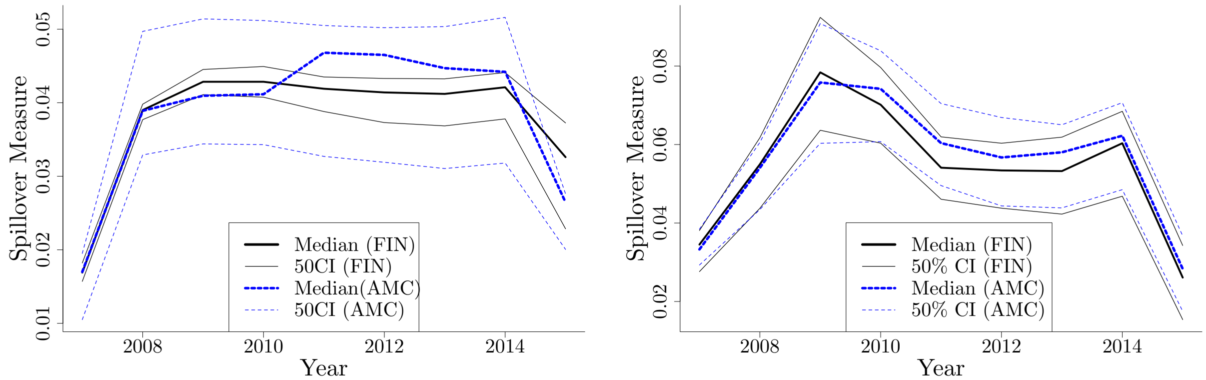
is very stable over time. It includes roughly 1050 institutions of which there are 44% banks (e.g., commercial and depository institutions), 15% brokers (e.g., investment banks and security dealers), 15% insurers, and 26% real estate firms (e.g., real estate operators). The total market capitalization of institutions in the FIN index is 8.4 trillion USD in 2015, and, thus, it seems to capture a very large fractions of all listed institutions worldwide.[31] Moreover, we employ the Datastream index for all American non-financial companies (AMC) as a proxy for the American real economy. We describe its composition in Appendix B.1.

Yearly firm-level data is retrieved from *A.M. Best Company*, *Thomson Reuters Worldscope*, and *ORBIS insurance focus*. Where available, we employ data from consolidated annual statements provided by *A.M. Best Company*, as this data is most detailed and granular. If not available, we choose data from either consolidated or unconsolidated statements in *ORBIS insurance focus*, or *Thomson Reuters Worldscope* in this order. Additionally, we employ annual reports of insurance holdings to cross-check and complement reported (life) insurance premiums, particularly due to inconsistencies in *ORBIS insurance focus*. *A.M. Best Company* and *ORBIS insurance focus* restrict access to firm-level data to 10 years and thus the panel is restricted to the years from 2006 to 2015. Since we employ a time-lag of one year between dependent and independent variables, the measures are computed for the years 2007 to 2015. All data is collected in U.S. dollar. After matching observations by year and ISIN number, our initial sample consists of 74 insurance companies.[32] This sample is smaller than in comparable studies (e.g., Bierth et al. (2015)), since observations particularly for life premiums written are very restricted. In order to study the impact of active reinsurance, we exclude companies without any observations for premiums for reinsurance assumed from our baseline sample. The names of the remaining 44 companies can be found in Table 12.

Figure 5 illustrates the evolution of the systemic risk measures over time for institutions in our baseline sample. Clearly, the financial crisis 2007-08 is related to a peak in the value of the measures, signaling a high level of short-term systemic risk. The median $-\Delta\text{CoVaR}^{\leq}$ does not decrease until 2015 in Figure 5 (a), while the Average Excess CoSP in Figure 5 (b) signals a decline in long-term systemic risk from 2010 on. These differences motivate the use of both measures in the empirical analysis.

[31] E.g., Fidelity reports that the market capitalization of U.S. financials is 7.5 trillion USD as of 11/17/2017 (`https://eresearch.fidelity.com/eresearch/markets_sectors/sectors/sectors_in_market.jhtml`).

[32] The names of the companies in our baseline sample can be found in Table 11.



(a) $-\Delta\text{CoVaR}^{\leq}$.

(b) Average Excess CoSP ($\bar{\psi}$).

Figure 5: Time evolution of systemic risk measures. The figure shows the median (bold) and 50% confidence interval around the median of the empirical distribution of each systemic risk measure with respect to either the global financial (FIN; straight lines) or American non-financial sector (AMC; blue dashed lines) across our baseline sample.

Moreover, the measures in Figure 5 also exhibit substantial differences between the financial (FIN) and non-financial (AMC) sector. These are particularly large for $-\Delta\text{CoVaR}^{\leq}$, as its volatility across insurance companies in our sample is larger with respect to the AMC than to the FIN index. Hence, there is a larger discrepancy between the systemic risk contribution of insurers for the non-financial sector than for the financial sector. An explanation might be that insurers are very differently interconnected with the non-financial sector. These differences motivate us to distinct between systemic risk with respect to the financial and to the non-financial sector.

Descriptive statistics of the systemic risk measures and explanatory variables are reported in Table 3. The mean value of the Average Excess CoSP in our sample is roughly 5%. Thus, an average insurer in our sample increases the average likelihood of a shock to the financial or non-financial system by 5 percentage points within 100 days after an insurer's distress. The empirical distribution of $-\Delta\text{CoVaR}^{\leq}$ implies that an average insurer in our sample increases the system's tail risk by about 3.7% during the insurer's financial distress. The average values of the $-\Delta\text{CoVaR}^{\leq}$ are larger than the average values of $-\Delta\text{CoVaR}$ in the study of Bierth et al. (2015) and similar to that of Weiß and Mühlnickel (2014). This suggests that our sample comprises of, on average, more systemically relevant insurers.

The average fraction of life business in our sample is 44.9%, which is very close to the median

Statistic	N	Min	Max	Median	Mean	St. Dev.
Average Excess CoSP ($\bar{\psi}$) (FIN)	525	0.001	0.118	0.054	0.053	0.022
Average Excess CoSP ($\bar{\psi}$) (AMC)	524	0.001	0.115	0.057	0.054	0.022
- ΔCoVaR$^{\leq}$ (FIN)	525	0.008	0.047	0.040	0.037	0.009
- ΔCoVaR$^{\leq}$ (AMC)	524	0.004	0.053	0.036	0.037	0.012
Life	525	0.000	1.000	0.444	0.449	0.381
Total Assets (billion USD)	525	1.367	1,562.117	47.111	138.707	223.008
Market-to-Book	525	0.192	4.022	1.142	1.330	0.694
RoE	525	-1.014	0.374	0.106	0.096	0.109
Leverage	525	1.266	163.186	8.247	11.974	13.843
Debt	525	0.000	16.448	0.382	0.657	1.425
Non-core Activities	522	0.000	440.151	1.283	2.632	19.537
Stocks	510	0.000	0.612	0.044	0.074	0.090
Reinsurance	319	0.000	1.000	0.023	0.159	0.297

Table 3: Descriptive statistics for systemic risk measures with respect to the global financial (FIN) and American non-financial (AMC) sector in the years 2007 to 2015, and company variables in the years 2006 to 2014 based on insurer-year observations. Source: *Thomson Reuters Worldscope*, *ORBIS insurance focus*, *A.M. Best Company*, and own calculations.

value (44.4%). This indicates that the average and median insurer in our sample conduct slightly more non-life than life business. However, the sample also includes insurance holdings that underwrite exclusively life insurance and no-life insurance, respectively, i.e., monoline insurers. This large range of companies and the relatively high standard deviation within our sample (38.1%) allows us to reliably identify the effect of business diversification on systemic risk.[33]

The average insurer's total assets is roughly 139 billion USD, which is substantially larger than the median value of 47 billion USD. To account for the skewness of the distribution, we employ the natural logarithm of total assets in the panel regressions. Comparing the distribution of total assets in our sample with that in similar studies (e.g., Bierth et al. (2015) and Weiß and Mühlnickel (2014)), we find that our sample is biased towards larger insurance companies. The (non-)availability of data about the fraction of life business is the main reason for us having a smaller sample than other studies. With this in mind, a larger average company size is not surprising if large insurers are more likely to report detailed balance sheet variables. The difference in size also explains why insurers in our sample exhibit higher values of systemic risk than in previous studies, as size is typically positively related to systemic risk.

The average insurer in our sample exhibits a market-to-book ratio of 1.3 (with median value 1.1), a return on equity of roughly 10% (with median value 11%), and a leverage (i.e., asset to

[33] For 278 insurer-year observations, the fraction of life premiums is strictly larger than 0 and smaller than 1.

equity market values) ratio of 12 (with median value 8). The first two do not substantially differ from those in the sample of Bierth et al. (2015) and Weiß and Mühlnickel (2014), while the leverage ratio is smaller in our sample. The mean debt-to-equity ratio is 0.66 (with median value 0.4), thus, the average insurer has issued debt that amounts to 66% of the book value of equity.

As the mean value of non-core activities (liabilities over insurance reserves) is 2.6, only roughly one third of the average insurer's total liabilities comprise of insurance reserves. The average insurer in our sample invests 7% of total investments in stocks. Average reinsurance assumed amounts to the size of 16% of total premiums written. These reinsurance premiums include both, life and non-life reinsurance business, although insurers typically cede more non-life than life insurance to reinsurers.[34] Since the minimum (maximum) value of *reinsurance* in our sample is zero (one), our sample includes pure direct insurers and pure reinsurers as well as insurance companies that conduct both primary insurance and reinsurance business.

The geographical distribution of the 74 insurers' headquarters in our baseline sample is as follows: 44% insurers are based in Europe (the largest proportions are in 8% in Switzerland, 7% in Italy, and 5% in Germany), 39% in North America (31% in the U.S. and 8% in Canada), 8% in Asia, 4% in Africa, 2% in Japan, and 2% in Australia.[35]

In Table B.2 in Appendix B.2 we report the correlation of variables. We find that the correlation between short-term and long-term systemic risk is 0.65 (0.73) with respect to the FIN (AMC) index, suggesting that the two systemic risk measures capture some similar patters in systemic risk. However, the systemic risk measures exhibit a very small negative correlation between systemic risk with respect to the FIN and to the AMC index, respectively. The independent variables also exhibit substantial differences in the degree of correlation across short- and long-term systemic risk and the FIN and AMC index. This suggests that the contribution to systemic risk on financial markets differs substantially from that on the real economy. The correlation between the independent variables is relatively small.

[34] Cummins and Weiss (2014) report that U.S. life (non-life) insurers ceded 18.1% (22.3%) of direct premiums written to reinsurers in 2012.

[35] The difference to a total of 100% is explained by rounding errors.

4.4 Life and Non-Life Business

Hypothesis ($H1$) states that more-diversified insurers have a smaller contribution to systemic risk. We examine this hypothesis in the following baseline OLS panel regression:

$$Y_{i,t} = \beta_0 + \beta_{life,1}\, Life_{i,t-1}^2 + \beta_{life,2}\, Life_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}. \tag{9}$$

$Y_{i,t}$ is the respective systemic risk measure with respect to the global financial (FIN) or American non-financial (AMC) sector. $Life_{i,t-1}$ refers to the insurer's fraction of gross premiums written in life business to total gross premiums written, and $Z_{t,t-1}$ to the insurer-specific control variables (log total assets, market-to-book ratio, return on equity, and leverage) at year $t-1$. To mitigate the possibility of reverse causality between the systemic risk measures and insurer characteristics, we lag all explanatory variables based on accounting statements by one year.[36] We include time-fixed effects β_t, and compute insurer-clustered standard errors.

The estimated coefficients are presented in Table 4. We find that the fraction of life business is significantly related to systemic risk. While this is in line with the results of Berdin and Sottocornola (2015), we also find that the quadratic term of life business is highly significant. Indeed, for both systemic risk measures we find that $\beta_{life,1} > 0$ and $\beta_{life,2} < 0$. This implies that more-diversified insurers have a smaller contribution to systemic risk, which confirms hypothesis ($H1$).

The effect of an insurer's size on systemic risk measures is in line with the results of Weiß and Mühlnickel (2014), Berdin and Sottocornola (2015), and Bierth et al. (2015), as larger insurers have a larger contribution to systemic risk. Interestingly, we find that insurers with higher leverage have a smaller contribution to systemic risk, which is in contrast to the results of Bierth et al. (2015). This finding suggests that a higher leverage, for a given distribution of premiums, primarily signals high insurance reserves that contribute to the stability of an insurance company. The effect of the market-to-book ratio tends to be negatively related to systemic risk, which suggests that a high profitability reduces the risk of systemic spillovers.

Although we find the relation between systemic risk and life business to be significantly non-linear, this does not necessarily imply a diversification effect since the implied quadratic function might still be increasing for all attainable values of the $Life$-variable. To test whether this is the

[36] Our results do not change if we instead lag explanatory variables by two years.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta$CoVaR$^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta$CoVaR$^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	4.385***	0.015***	5.448***	0.032***
	(1.446)	(0.006)	(1.478)	(0.009)
Life	$-$4.767***	$-$0.016**	$-$5.691***	$-$0.033***
	(1.603)	(0.007)	(1.644)	(0.010)
Log.Total.Assets	0.174*	0.002***	0.232**	0.003***
	(0.093)	(0.0003)	(0.094)	(0.001)
Market.to.Book	$-$0.233	$-$0.001	$-$0.334	$-$0.003*
	(0.195)	(0.001)	(0.214)	(0.002)
RoE	$-$1.213	$-$0.002	$-$0.835	$-$0.003
	(1.655)	(0.003)	(1.657)	(0.006)
Leverage	$-$0.010	$-$0.0001*	$-$0.014	$-$0.0002***
	(0.015)	(0.00004)	(0.014)	(0.0001)
Constant	1.322	$-$0.009*	0.406	$-$0.029***
	(1.631)	(0.005)	(1.661)	(0.010)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1908.3	$-$4023.6	1920.8	$-$3524.1
Observations	525	525	524	524
R^2	0.552	0.647	0.541	0.575
Adjusted R^2	0.540	0.637	0.529	0.563
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Baseline OLS Regression (9) for Insurance Business.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent ΔCoVaR$^{\leq}$ with respect to the global financial sector (FIN) and to the American non-financial sector (AMC), respectively. Robust standard errors are clustered by insurers and reported in parentheses.

case, we compute the implied systemic risk-minimizing fraction of life business. This is given as the minimum to the function $Y_{i,t}$ in Equation (9) with respect to Life and results from the first-order condition:

$$\alpha_L^* = -\frac{\beta_{life,2}}{2\beta_{life,1}}. \tag{10}$$

In Table 5 we report the resulting systemic risk-minimizing fractions of life business α_L^* for different measures and sectors. First, we observe that α_L^* is larger than 50% for all combinations of systemic risk measures and sectors. This confirms hypothesis ($H2$) and is consistent with life business having a smaller volatility than non-life business. Thus, an average insurance holding that underwrites slightly more than 50% of premiums in life business has the smallest contribution to systemic risk. Second, the systemic risk-minimizing fraction of life business (α_L^*) is very similar across different measures and with respect to different sectors. This finding confirms the robustness of our results.

Systemic Risk Measure	FIN	AMC
Average Excess CoSP	0.54	0.52
$-\Delta\text{CoVaR}^{\leq}$	0.52	0.51

Table 5: Systemic risk-minimizing fraction of life business (α_L^*) implied by baseline panel regressions with respect to the global financial (FIN) and American non-financial (AMC) sector.

The impact of life insurance is not only statistically significant in our baseline model, it is also economically significant: If an average insurer's fraction of premiums written in life business deviates by one standard deviation from the systemic risk-minimizing fraction α_L^*, its contribution to long-term systemic risk (as measured by the Average Excess CoSP) grows by roughly 38%, and that to short-term systemic risk (as measured by $-\Delta\text{CoVaR}^{\leq}$) grows by 9% to 24%. The sensitivities are reported in Table 6. These findings highlight the importance of life business particularly for long-term systemic risk: As the long duration of life insurance contracts increases the long-term stability of cash flows, diversification of business activities is more important for long-term than short-term systemic risk.

Systemic Risk Measure	FIN	AMC
Average Excess CoSP	34%	42%
$-\Delta\text{CoVaR}^{\leq}$	9%	25%

Table 6: Relative change in systemic risk with respect to the global financial (FIN) and American non-financial (AMC) sector upon a change in the fraction of life business by one standard deviation from the systemic risk-minimizing fraction of life business (α_L^*) for the average insurer in our baseline sample.

In contrast to our baseline model, the relation between systemic risk measures and explanatory variables might be nonlinear. Since $\Delta\text{CoVaR}^{\leq}$ reflects the quantile of log returns, we examine additional panel regressions with $\exp(\Delta\text{CoVaR}^{\leq})$ as dependent variable, which might be interpreted as a gross rate of return. Large values of the Average Excess CoSP, $\bar{\psi}$, might result from outliers of CoSP (Kubitza and Gründl (2017)). To account for this possibility, we give more weight to differences in small values of $\bar{\psi}$ by additionally examining $\log(\bar{\psi})$. The estimated coefficients for these two regression set-ups can be found in Table 15 in Appendix B.3. Our baseline results remain the same.[37] Furthermore, in unreported regressions we also employ a Generalized Linear Model (GLM) with gamma distributed errors and logarithmic link function, which yields the same results, as well. Most importantly, the (quadratic) impact of the fraction life business remains highly statistically significant and positive in all model set-ups.[38] Furthermore, we account for potential outliers with respect to the return on equity, and find that winsoring our sample does not have an impact on our results.

We employ the fraction of gross premiums written in life business as a proxy for the relative size of life business of an insurance holding. In contrast to net premiums, gross premiums do not exclude business that has been ceded to a reinsurer. However, ceding part of the insurance business reduces the (tail) risk remaining on a primary insurer's balance sheet and, thus, might have an impact on systemic risk. To test whether our findings are sensitive to the definition of life business, we replace the fraction of gross premiums written by net premiums written in our baseline model. The estimated coefficients can be found in Table 16 in Appendix B.3. Our baseline results are confirmed.

Another alternative measure for the relative size of life business are insurance reserves. However, insurance reserves do not accurately reflect the distribution of cash flows: A high ratio of life insurance reserves relative to total reserves might not only reflect a large number of life insurance policies sold but also a long duration of life policies. Since in our model in Section 3 financial contagion primarily depends on the distribution of cash flows, we do not expect insurance reserves do be a good proxy for the relative size of life business cash flows. In an unreported panel regression we replace the proportion of life premiums by that of life reserves for U.S. insurance holdings as reported by A.M. Best Company from 2006 to 2014. Indeed, we do not find a significant diversification effect between life and non-life reserves, and only a very weak effect of life reserves on systemic risk in general. This finding confirms that diversification of business activities is mainly caused by diversification of cash flows.

In our baseline regressions we do not include insurer-fixed effects. Without insurer-fixed effects, we are able to base our estimation on cross-sectional differences between insurers. Since most

[37]Interestingly, the significance of the control variables as well as the goodness of fit (as measured by a decrease in Akaike's information criterion) increases substantially in this robustness set-up, particularly for $\exp(\Delta\text{CoVaR}^{\leq})$.

[38]We also employ both additional regression set-ups to confirm the robustness of other OLS regressions in this article. The results are available on request by the authors.

explanatory variables are very persistent over time for each insurer, including insurer-fixed effects would dramatically reduce the heterogeneity in our sample.[39] This would substantially increase the parameter uncertainty in our model and, thus, reduce the statistical significance of the coefficients. Indeed, including insurer-fixed effects raises R^2 up to 93% and renders all explanatory variables insignificant at the 5% level.[40] This suggests substantial overfitting of the model.

Therefore, we mainly rely on cross-sectional differences between insurance companies. In fact, we derive similar results when we focus on only one year of our sample. In Table 17 in Appendix B.3 we report the estimated coefficients for our baseline regression within 2015 (due to the time-lag in the regression, explanatory variables are from 2014). The results confirm our baseline regression. Moreover, since in these cross-sectional regressions the first year that is used for the estimation of the systemic risk measures is 2009, this analysis also suggests that the financial crisis 2007-2008 (including the near-default of AIG) is not a driver for our baseline results.[41]

Systemic risk might depend on the location of insurers. U.S. insurers in particular might exhibit a larger degree of risk with respect to the American non-financial sector (AMC) than European insurers. To account for such geographic effects, we conduct an additional regression with continent-fixed effects. The estimated coefficients can be found in Table 18 in Appendix B.3. Indeed, we find significant differences in the systemic risk particularly between African, Australian, Japanese and European insurers, respectively. Differences between European and North American insurers are significant particularly for short-term systemic risk with respect to the American non-financial sector. Moreover, in all regressions except for $\Delta\text{CoVaR}^{\leq}$ (AMC) we still find the quadratic term of life business to be significantly positive and the linear term to be significantly negative. The implied systemic risk-minimizing fractions of life business remain close to our baseline results.

One concern about the use of systemic risk measures is that these can be highly correlated with systematic risk or idiosyncratic risk (Benoit et al. (2017)). Thus, our results might be driven by correlation between an insurer's assets and financial market movements. As Kubitza and Gründl (2017) show, this issue is more relevant for $\Delta\text{CoVaR}^{\leq}$ as it relies on contemporaneous correlation.

[39] Note that we control for the persistence of variables by computing standard errors clustered by insurers. Also, an unreported robustness check with including the one year-lagged systemic risk measures in the regression produces similar results.

[40] Also, all variables except for leverage with respect to $\Delta\text{CoVaR}^{\leq}$ (AMC) are insignificant at the 10% level.

[41] Moreover, note that AIG is not part of our sample as it does not report gross written premiums in life insurance. Thus, we are not concerned that AIG might bias our results.

Therefore, if indeed our results were driven by systematic risk, we would expect this effect to be particularly large with respect to $\Delta\text{CoVaR}^{\leq}$. However, Table 6 shows that the impact of diversification is particularly large with respect to the Aggregate Excess CoSP. For this reason, we find it unlikely that systematic risk drives our results.

4.5 Non-Core Insurance Activities

Life insurers typically conduct more non-core activities in excess of underwriting insurance contracts than non-life insurers.[42] This provides an alternative explanation for the trade off between life and non-life business (The Geneva Association (2010), Cummins and Weiss (2014)). If non-core insurance activities were explaining our results, controlling for these would render the quadratic term of life business insignificant.

Indeed, we find that non-core activities tend to exhibit a positive relation with long-term systemic risk (see Table 19 in Appendix B.3). However, these activities neither alter the significance of the quadratic interaction between systemic risk and the fraction of life business nor impact the implied systemic risk-minimizing fraction of systemic risk, as reported in Table 7. We conclude that non-core activities do not explain our results.

Systemic Risk Measure	FIN	AMC
Average Excess CoSP	0.53	0.51
$-\Delta\text{CoVaR}^{\leq}$	0.51	0.51

Table 7: Systemic risk-minimizing fraction of life premiums, α_L^*, implied by panel regressions with respect to the global financial (FIN) and American non-financial (AMC) sector after controlling for non-core activities.

4.6 Investment Volatility

As a measure for the volatility of an insurance holding's investment return, we employ the total fraction of equity stock investments in a particular year. We interact life business with stocks in

[42]For example, according to the Board of Governors of the Federal Reserve System (2017), in the first quarter of 2017 the average U.S. life (non-life) insurer engaged in security lending activities by 0.8% (0.4%) and in loan activities by 1.1% (0.3%) relative to total liabilities.

the following regression model:

$$
\begin{aligned}
Y_{i,t} =& \beta_0 + \beta_{life,1}\, Life^2_{i,t-1} + \beta_{life,2}\, Life_{i,t-1} + \beta_{life,stocks}\, Life_{i,t-1} * Stocks_{i,t-1} \\
&+ \beta_{stocks}\, Stocks_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}.
\end{aligned} \tag{11}
$$

The results can be found in Appendix B.3 in Table 20. The systemic risk-minimizing fraction of life business in this model is given as

$$
\alpha_L^* = -\frac{\beta_{life,2} + \beta_{life,stocks} Stocks}{2\beta_{life,1}}. \tag{12}
$$

We find that the interaction term, $\beta_{life,stocks}$, tends to be negative but significantly different from zero at the 10% level only for $-\Delta\text{CoVaR}^{\leq}$ (AMC) (see Table 20). Hence, since it is $\beta_{life,1} > 0$, the systemic risk-minimizing fraction α_L^* tends to increase with stock investments, which is consistent with hypothesis ($H3$). Thus, if investment volatility increases, the proportion of life business for an insurer with the smallest contribution to systemic risk is larger. This is consistent with a *flight to safety* behavior.

Nevertheless, due to the low significance of the interaction term ($\beta_{life,stocks}$), we find that investment volatility only exhibits a weak effect on diversification between insurance business. This result suggests that diversification is mainly caused by the underlying insurance activities instead of investment activities. In an unreported regression, we also control for a non-linear effect of stock investments by interacting it with Life^2 as well. The results remain unchanged.

4.7 Debt

The theoretical model suggests that the systemic risk-minimizing fraction of life insurance is smaller for insurers with a higher debt-to-equity ratio (hypothesis (($H4$)). We examine whether this hypothesis is empirically supported by interacting debt and life business in the following regression:

$$
\begin{aligned}
Y_{i,t} =& \beta_0 + \beta_{life,1}\, life^2_{i,t-1} + \beta_{life,2}\, Life_{i,t-1} + \beta_{life,debt}\, Life_{i,t-1} * Debt_{i,t-1} \\
&+ \beta_{debt}\, Debt_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}.
\end{aligned} \tag{13}
$$

The results can be found in Appendix B.3 in Table 21. The systemic risk-minimizing fraction of life business in this model is given as

$$\alpha_L^* = -\frac{\beta_{life,2} + \beta_{life,debt} Debt}{2\beta_{life,1}}. \tag{14}$$

Since $\beta_{life,1} > 0$ and $\beta_{life,debt} < 0$ in Table 21, our results imply that α_L^* is increasing with an insurer's debt-to-equity ratio for all systemic risk measures. This suggests that insurers with a higher debt-to-equity ratio have the smallest contribution to systemic risk for a higher fraction of life business. This is consistent with hypothesis $(H4)$. Again, the result is similar to a *flight to safety*. However, as $\beta_{life,debt}$ is not significantly different from zero at the 10% level, we find that it does not have an important effect on diversification.

4.8 Reinsurance Business

Since primary insurance and reinsurance liabilities are strongly correlated, in hypothesis $(H5)$ we do not expect a diversification effect between primary insurance and active reinsurance business with respect to systemic risk. Indeed, in Table 22 in Appendix B.3 we do not find a significant quadratic interaction between reinsurance business assumed and systemic risk.[43]

However, given that reinsurance typically captures the tail risk of primary insurers, active reinsurance business might intensify the diversification between life and non-life business (hypothesis $(H6)$). We interact life business with reinsurance business in the following regression model

$$\begin{aligned} Y_{i,t} = \beta_0 &+ \beta_{life,1}\, Life_{i,t-1}^2 + \beta_{life,2}\, Life_{i,t-1} + \beta_{life,reins,2}\, Life_{i,t-1} * Reinsurance_{i,t-1} \\ &+ \beta_{reins}\, Reinsurance_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}. \end{aligned} \tag{16}$$

The estimated coefficients can be found in Table 23 in Appendix B.3. Although we do not find the interaction between reinsurance and life business to be statistically significant, reinsurance tends to increase the diversification benefit of life insurance business since $\beta_{life,reins,2} < 0$. Thus, insurers with a larger reinsurance business have the smallest contribution to systemic risk with a larger

[43] Table 22 in Appendix B.3 reports the results of the OLS regression

$$Y_{i,t} = \beta_0 + \beta_{reins,1} Reinsurance_{i,t-1}^2 + \beta_{reins,2} Reinsurance_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}. \tag{15}$$

$\beta_{reins,1}$ and $\beta_{reins,2}$ are not significantly different from zero at the 10% level.

fraction of (primary and reinsurance) life business. Again, this is a *flight to safety*-type of behavior.

5 Costs and Benefits of Diversification and Policy Implications

Our results suggest that diversification of life and non-life insurance activities reduce the systemic risk contribution of insurance companies. The average size of life business in our sample is slightly smaller than the level we have found to minimize systemic risk on average.[44] This observation raises two important questions, namely whether macro-prudential regulation should incentivize diversification of insurance activities, and what costs and benefits for the companies themselves are associated with differences in their business mix.

Wagner (2010) addresses the first question in a model of two banks. He shows that diversification of both banks raises the probability of systemic crises. A similar argument is laid out by Wagner (2008) as more homogenized institutions tend to invest more in risky projects at the costs of holding liquidity, which increases the likelihood of liquidity shortages and systemic crises. The main intuition is that, if both banks fully diversify, they will hold identical portfolios and either fail or do not fail together. One central assumption in both studies is that higher homogenization increases the correlation of exposures.

This assumption is not necessarily fully applicable to the insurance sector: First, the majority of different policyholders' claims is typically uncorrelated, for example claims from car accidents or private liability insurance.[45] Second, large claims resulting from catastrophic events, e.g. earthquakes, are correlated only among policyholders in the affected region. Thus, two insurance holdings A and B can diversify their insurance activities along the lines of life and non-life insurance in different geographic areas without being exposed to the same claims.

Therefore, a more homogeneous business mix of insurance companies can have an ambiguous effect on systemic risk: On the one hand, the exposure of insurers in a particular region might become more correlated when these engage in the same insurance activities. This applies mostly to catastrophic events that affect many policyholders simultaneously. Then, a high degree of correlation

[44] The average insurer in our sample underwrites 45% of premiums in life insurance, while the baseline regressions in Section 4.4 suggest that an average insurer with a fraction of roughly 51% of life business has the smallest systemic risk.

[45] Often, insurers even prohibit the insurance of the same risk at two different insurance companies in order to mitigate moral hazard, i.e. incentives for policyholders to increase the likelihood or size of a claim.

among exposures might raise the likelihood of joint failures and systemic crises within the insurance sector. On the other hand, since most catastrophic events are reinsured and non-catastrophic claims have a low correlation, diversification of insurance activities might reduce the systemic risk contribution of insurance companies with respect to other financial institutions. The low correlation of claims in particular suggests that the beneficial effect of business activity diversification is larger for insurers than for banks.

While diversification reduces business volatility, it might also evoke costs to insurers and policyholders. For example, consider one monoline and one multiline insurance company that have the same size. Then, the monoline insurance company will typically have a higher degree of diversification within its lines of business, as it sells more similar contracts within each line to different policyholders. This effect is commonly referred to as risk pooling or *economies of scale with respect to risk taking*, and enables the monoline insurer to offer a smaller premium for the same level of default risk as the multiline company (Cummins (1974)). Thus, policyholders might benefit from lower prices of monoline insurers compared to multiline insurers of the same size. If, in contrast, prices of monoline and multiline insurers were comparable, e.g., due to a high degree of competition, monoline insurers would have to hold less capital than multiline insurers for the same contract, which might decrease financing costs.

Diversification between insurance activities, on the other hand, is associated with economies of scope in terms of volatility. Similarly to economies of scale, diversification of insurance activities might reduce default risk and financing costs. Hence, the difference between multiline and monoline insurers is characterized by a trade-off 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.

We examine this trade-off with respect to measures of profitability, namely the return on assets and equity, of insurance holdings. We find a quadratic and u-shaped effect of the fraction of life business on profitability. It is significant at the 1% level for the return on assets.[46] This result suggests that a monoline insurer's profitability is larger than that of a multiline insurance company. It supports the view that economies of scale dominate economies of scope with respect to the profitability of insurance companies and, thus, is similar to the results that Stiroh (2004),

[46]The estimated coefficients can be found in Table 24 in Appendix B.3.

Stiroh and Rumble (2006), Laeven and Levine (2007) derive with respect to banks. Our finding is also in line with the results of Cummins et al. (2010) and Eling and Luhnen (2010) that multiline insurers are not necessarily more cost-efficient than monoline insurers.

6 Conclusion

In this article, we examine the impact of a financial institution's business mix on its contribution to systemic risk, i.e. the propensity to transmit economic shocks to other institutions. For this purpose, we focus on insurance companies since different insurance lines are typically similar in the type of business but exhibit a low degree of correlation.

We identify two stylized differences between non-life and life insurance business, namely that returns from life insurance are less volatile and potentially larger on expectation than from non-life insurance. By mapping these stylized differences in a simplified portfolio model for an insurance holding, we identify a diversification effect between life and non-life insurance business with respect to counterparty credit risk. The intuition is that credit risk can be minimized by means of the holding's return volatility. Since credit risk can be a contagion mechanism for the transmission of economic shocks, diversification between life and non-life insurance business does not only impact credit risk but also systemic risk in general.

Our model predicts that insurers that underwrite slightly more than 50% of premiums in life business exhibit the smallest contribution to systemic risk. This systemic risk-minimizing fraction is increasing with the volatility of investments and an insurer's debt-to-equity ratio. We confirm these predictions in an empirical analysis of international insurance companies by means of systemic risk measures, and demonstrate their robustness towards several model specifications. Moreover, we provide empirical evidence that the low volatility of life business can compensate for the high tail risk of reinsurance business with respect to systemic risk.

The results in this article contribute to the discussion on how to decrease systemic risk among financial institutions. Our findings suggest that macro-prudential regulation should reward a diversified business mix as long as an increase in common exposures is limited. Since the systemic risk-minimizing fraction of life business is likely to differ across insurers, regulation should however not impose one desired fraction of life business for all institutions. In contrast, macro-prudential policies should rather aim at stabilizing particularly those insurance holdings that are not well-diversified in their business activities. Indeed, monoline insurers experienced substantial financial distress in the dawn of the 2007-08 financial crisis (Brunnermeier (2009)). A similar rationale applies to the risk management of institutions that engage in financial transactions with an insurer in the sense that diversification of the insurer's business activities can reduce counterparty credit risk.

A Proofs

Lemma 1. *If the expected returns from life and non-life business do not differ, the credit-risk minimizing fraction of life business is given as*

$$\alpha_L^* = \frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho}. \tag{17}$$

It is $\alpha_L^* \in (0,1)$ *if* $\rho < \min\left(\frac{\sigma_{NL}}{\sigma_L}, \frac{\sigma_L}{\sigma_{NL}}\right)$. α_L^* *is decreasing (increasing) with the return volatility of the life (non-life) business, if* ρ *is sufficiently small.*

If $\rho > \geq$ *and* $\sigma_L < \sigma_{NL}$, *it is* $\alpha_L^* > 0.5$.

Proof. The marginal expected loss is equal to

$$\frac{dEL}{d\alpha_L} = -\frac{d\mu}{d\alpha_L} \Phi\left(\frac{D-\mu}{\sigma}\right) + \frac{d\sigma}{d\alpha_L} \varphi\left(\frac{D-\mu}{\sigma}\right). \tag{18}$$

Since we assume the expected return to be independent from α_L, the first-order condition (FOC) for a minimum is given as

$$\frac{d\sigma}{d\alpha_L} = 0. \tag{19}$$

Since $\frac{d\sigma}{d\alpha_L} = \frac{1}{2}\sigma^{-1}\frac{d\sigma^2}{d\alpha_L}$ and $\sigma > 0$, the FOC is equivalent to

$$\frac{d\sigma^2}{d\alpha_L} = 0 \tag{20}$$

$$2\alpha_L \sigma_L^2 - 2(1-\alpha_L)\sigma_{NL}^2 + 2(1-2\alpha_L)\sigma_L \sigma_{NL} \rho = 0 \tag{21}$$

$$\alpha_L\left(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho\right) - \sigma_{NL}^2 + \sigma_L \sigma_{NL} \rho = 0 \tag{22}$$

$$\alpha_L^* = \frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho} \tag{23}$$

It is straightforward to verify the second-order condition that α_L^* is a minimum for EL. Since $(\sigma_L - \sigma_{NL})^2 > 0$, it is $\frac{\sigma_L^2 + \sigma_{NL}^2}{2\sigma_L \sigma_{NL}} > 1$ and thus $\rho < \frac{\sigma_L^2 + \sigma_{NL}^2}{2\sigma_L \sigma_{NL}}$ or, equivalently, $\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho > 0$.

Thus, it is

$$
\begin{aligned}
&\frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho} < 1 && (24)\\
\Leftrightarrow\quad & \sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho < \sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho && (25)\\
\Leftrightarrow\quad & 0 < \sigma_L \left(\sigma_L - \sigma_{NL} \rho\right) && (26)\\
\Leftrightarrow\quad & \rho < \frac{\sigma_L}{\sigma_{NL}} && (27)
\end{aligned}
$$

and

$$
\begin{aligned}
&\frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho} > 0 && (28)\\
\Leftrightarrow\quad & \sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho > 0 && (29)\\
\Leftrightarrow\quad & \frac{\sigma_{NL}}{\sigma_L} > \rho && (30)
\end{aligned}
$$

A marginal change in the life return volatility yields

$$
\begin{aligned}
\frac{d\alpha_L^*}{d\sigma_L} &= \frac{-\sigma_{NL}\rho(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho) - (\sigma_{NL}^2 - \sigma_L\sigma_{NL}\rho)(2\sigma_L - 2\sigma_{NL}\rho)}{(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho)^2} && (31)\\
&= \frac{\sigma_{NL}\rho\sigma_L^2 - \sigma_{NL}\rho\sigma_{NL}^2 - \sigma_{NL}^2(2\sigma_L - 2\sigma_{NL}\rho)}{(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho)^2} && (32)\\
&= \sigma_{NL}\frac{\rho(\sigma_L^2 + \sigma_{NL}^2) - 2\sigma_{NL}\sigma_L}{(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho)^2}, && (33)
\end{aligned}
$$

which is negative if $\rho < \frac{2\sigma_{NL}\sigma_L}{\sigma_L^2+\sigma_{NL}^2}$. Since $1 - \alpha_L^* = \frac{(\sigma_L)^2 - \sigma_L\sigma_{NL}\rho}{\sigma_L^2+\sigma_{NL}^2-2\sigma_L\sigma_{NL}\rho}$, $1-\alpha_L^*$ is decreasing and α_L^* increasing in σ_{NL} if ρ is sufficiently small.

Since $(\sigma_L - \sigma_{NL})^2 > 0$, it is $\frac{\sigma_L^2+\sigma_{NL}^2}{2\sigma_L\sigma_{NL}} > 1$ and thus $\rho < \frac{\sigma_L^2+\sigma_{NL}^2}{2\sigma_L\sigma_{NL}}$ or, equivalently, $\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho$. As shown in Lemma 1, the credit-risk minimizing fraction is given by

$$
\begin{aligned}
&\frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho} > 1/2 && (34)\\
\Leftrightarrow\quad & 2\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho > \sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho && (35)\\
\Leftrightarrow\quad & \frac{\sigma_{NL}^2 - \sigma_L^2}{\sigma_L\sigma_{NL}} > -\rho, && (36)
\end{aligned}
$$

which holds if $\sigma_L < \sigma_{NL}$ and $\rho > 0$. $\square$

Lemma 2. *Assume that the return from life business is less volatile and larger in expectation than that from non-life business. If the debt-to-equity ratio is sufficiently large, it is* $\alpha_L^* = 1$.

Proof. The return volatility is given by

$$\sigma^2 = \alpha_L^2\sigma_L^2 + (1-\alpha_L)^2\sigma_{NL}^2 + 2\alpha_L(1-\alpha_L)\sigma_L\sigma_{NL}\rho \tag{37}$$

and the expected return by

$$\mu = \alpha_L\mu_L + (1-\alpha_L)\mu_{NL}. \tag{38}$$

For increasing D it is

$$\lim_{D\to 1}\frac{D-\mu}{\sigma} = \lim_{D\to\infty}\frac{D-(\alpha_L\mu_L+(1-\alpha_L)\mu_{NL})}{\sqrt{\alpha_L^2\sigma_L^2 + (1-\alpha_L)^2\sigma_{NL}^2 + 2\alpha_L(1-\alpha_L)\sigma_L\sigma_{NL}\rho}} \tag{39}$$

$$= \infty \tag{40}$$

and, thus, $\Phi\left(\frac{D-\mu}{\sigma}\right) \to 1$ and $\varphi\left(\frac{D-\mu}{\sigma}\right) \to 0$. Therefore, if D is sufficiently large, it is $EL \approx D-\mu$, which is minimized at $\alpha_L = 1$ if $\mu_L > \mu_{NL}$. $\square$

B Empirical Analysis

B.1 System's Index

As in Kubitza and Gründl (2017), we compute the index of the global financial system by excluding the currently considered institution j. By weighting the total (divident-adjusted) return index of institution i, TR, by the relative market capitalization (in USD) of institution i at time t, MC, the index for the financial system $\mathbb{S}$ of institutions is given as

$$INDEX_t^{\mathbb{S}|j} = INDEX_{t-1}^{\mathbb{S}|j}\sum_{s\in\mathbb{S}\setminus\{j\}}\frac{MC_{s,t-1}}{\sum_{i\in\mathbb{S}\setminus\{j\}}MC_{i,t-1}}\frac{TR_{s,t}}{TR_{s,t-1}}. \tag{41}$$

To compute the return based systemic risk measures, we employ the log return, $\log(INDEX_t^{\mathbb{S}|j}/INDEX_{t-1}^{\mathbb{S}|j})$.

In the index for the global financial system (FIN), we include all financial institutions in Datastream that 1) exhibit more than 1500 observations of the total return during the whole considered period to ensure sufficient liquidity and consistency of the data, and 2) are either alive in 2016 or dead in 2016 but listed in the previous period in one of the five largest global markets (United States, Germany, United Kingdom, China, and Japan).[47] The number and type of institutions used to construct the resulting index (FIN) is shown in Table 8.

Time Period	Absolute Number of Institutions	Total Market Cap. (trillion USD)	Fraction of Banks	Fraction of Brokers	Fraction of Insurers	Fraction of Real Estate Firms
2015	1044	8.41	44.3%	14.3%	15.1%	26.2%
2014	1054	7.82	44.2%	14.8%	14.9%	26.1%
2013	1058	7.75	44.1%	15.2%	14.8%	25.8%
2012	1062	7.68	43.9%	15.3%	15.1%	25.7%
2011	1071	7.68	43.7%	16%	14.9%	25.4%
2010	1074	7.59	43.8%	16%	14.9%	25.3%
2009	1071	7.2	43.8%	16.3%	14.6%	25.3%
2008	1040	6.66	43.2%	16.8%	14.4%	25.6%
2007	1031	6.75	43.2%	16.9%	14.4%	25.6%

Table 8: Number and type of institutions used to construct the global financial system index (FIN). We classify an institution as bank (i.e. commercial bank, or depository institution) if its SIC is 6021, 6022, 6029, 6035, 6036, 6061, 6062, 6081, or 6082, broker (i.e. non-depository credit institution, investment bank, or security and commodity broker) if its SIC is between 6100 and 6280, insurer (i.e., insurance carrier) if its SIC is between 6300 and 6400, or as real estate firm (i.e. real estate property operators, developer, agents, or managers) if its SIC is between 6500 and 6600.

The Datastream American non-financial index consists of 1260 institutions from 33 different industrial sectors and 9 geographic locations. Table 9 depicts the 10 largest companies of the index in a descending order and Table 10 provides information on the 5 largest sectors as well as geographic locations.

[47] We choose this restriction to narrow down the resulting amount of data.

Top 10 Companies	Industrial Sectors
APPLE	Technology Hardware and Equipment
EXXON MOBIL	Oil and Gas Producers
MICROSET	Software and Computer Services
GENERAL ELECTRIC	General Industrials
JOHNSON & JOHNSON	Pharmaceuticals and Biotechnology
WAL MART STORES	General Retailers
CHEVRON	Oil and Gas Producers
PROCTER & GAMBLE	Household Goods and Home Construction
INTERNATIONAL BUSINESS MACHINES	Software and Computer Services
ALPHABET 'C'	Software and Computer Services

Table 9: List of the 10 largest institutions in descending order according to the Datastream American non-financial market index w.r.t. to the average value of their monthly market value in USD over the period 2010-2015.

Top 5 Industrial Sectors	Top 5 Geographic Locations
General Retailers (6.1 %)	United States of America (60.4 %)
Electricity (6.1 %)	Canada (15.5 %)
Oil and Gas Producers (6.0 %)	Brazil (6.2 %)
Software and Computer Services (5.8 %)	Mexico (5.3 %)
Food Producers (4.5 %)	Argentina (3.0 %)

Table 10: List of the 5 largest industrial sectors and geographic locations in the Datastream American non-financial market index according to the number of companies included.

B.2 Data

	Name	Name
1	AEGON	MENORA MIV HOLDING
2	AFLAC	METLIFE
3	ALLEGHANY	MGIC INVESTMENT
4	ALLIANZ	MIGDAL INSURANCE
5	ALLSTATE	MMI HOLDINGS
6	AMERICAN FINL.GP.OHIO	MS&AD INSURANCE GP.HDG.
7	AMERICAN INTL.GP.	MUENCHENER RUCK.
8	AMTRUST FINL.SVS.	PERMANENT TSB GHG.
9	ANADOLU HAYAT EMEKLILIK	PHOENIX INSURANCE 1
10	ASSICURAZIONI GENERALI	PRINCIPAL FINL.GP.
11	ASSURED GUARANTY	PROGRESSIVE OHIO
12	AXA	QBE INSURANCE GROUP
13	AXIS CAPITAL HDG.	REINSURANCE GROUP E AM.
14	BALOISE-HOLDING AG	SAMPO 'A'
15	CATTOLICA ASSICURAZIONI	SANLAM
16	CHINA LIFE INSURANCE 'H'	SANTAM
17	CLAL INSURANCE	SCOR SE
18	CNA FINANCIAL	STOREBRAND
19	CNO FINANCIAL GROUP	SUN LIFE FINL.
20	CNP ASSURANCES	SWISS LIFE HOLDING
21	DELTA LLOYD GROUP	SWISS RE
22	DISCOVERY	TOKIO MARINE HOLDINGS
23	EULER HERMES GROUP	TOPDANMARK
24	FAIRFAX FINL.HDG.	TORCHMARK
25	FBD HOLDINGS	TRAVELERS COS.
26	GREAT WEST LIFECO	TRYG
27	GRUPO CATALANA OCCIDENTE	UNIPOL GRUPPO FINANZIARI
28	HANNOVER RUCK.	UNIPOLSAI
29	HANOVER INSURANCE GROUP	UNIQA INSU GR AG
30	HAREL IN.INVS.& FNSR.	UNUM GROUP
31	HELVETIA HOLDING N	VAUDOISE 'B'
32	INTACT FINANCIAL	VIENNA INSURANCE GROUP A
33	LIBERTY HOLDINGS	VITTORIA ASSICURAZIONI
34	LINCOLN NATIONAL	W R BERKLEY
35	LOEWS	WUESTENROT & WUERTT.
36	MANULIFE FINANCIAL	ZURICH INSURANCE GROUP
37	MAPFRE	
38	MARKEL	

Table 11: List of all insurance companies included in regressions without reinsurance business or long-term bonds as independent variable.

The sample is constructed by matching firm-level data from *Thomson Reuters Worldscope*, and *ORBIS Insurance Focus* by year and ISIN number.

	Name	Name
1	ALLEGHANY	MARKEL
2	ALLIANZ	METLIFE
3	ALLSTATE	MGIC INVESTMENT
4	AMERICAN INTL.GP.	MUENCHENER RUCK.
5	AMTRUST FINL.SVS.	PRINCIPAL FINL.GP.
6	ASSICURAZIONI GENERALI	QBE INSURANCE GROUP
7	ASSURED GUARANTY	REINSURANCE GROUP E AM.
8	AXA	SAMPO 'A'
9	AXIS CAPITAL HDG.	SCOR SE
10	BALOISE-HOLDING AG	SWISS LIFE HOLDING
11	CATTOLICA ASSICURAZIONI	SWISS RE
12	CHINA LIFE INSURANCE 'H'	TRAVELERS COS.
13	CNA FINANCIAL	UNIPOL GRUPPO FINANZIARI
14	CNO FINANCIAL GROUP	UNIPOLSAI
15	EULER HERMES GROUP	UNIQA INSU GR AG
16	FAIRFAX FINL.HDG.	VAUDOISE 'B'
17	GRUPO CATALANA OCCIDENTE	VIENNA INSURANCE GROUP A
18	HANNOVER RUCK.	VITTORIA ASSICURAZIONI
19	HANOVER INSURANCE GROUP	W R BERKLEY
20	HELVETIA HOLDING N	WUESTENROT & WUERTT.
21	LINCOLN NATIONAL	ZURICH INSURANCE GROUP
22	MAPFRE	

Table 12: List of all insurance companies included in regressions with reinsurance business as independent variable.

The sample is constructed by matching firm-level data from *Thomson Reuters Worldscope*, and *ORBIS Insurance Focus* by year and ISIN number.

Variable name	Definition	Data source
Dependent variables		
Average Excess CoSP ($\overline{\psi}$)	Average extent to which an institution's distress increases the likelihood of a system's distress within 100 days after the institution's distress event.	Datastream, own calc.
Dependence-consistent $\Delta\text{CoVaR}^{\leq}$	Difference between a system's Value-at-Risk (VaR) conditional on an institution being in distress and the system's VaR conditional on the institution's benchmark state.	Datastream, own calc.
Explanatory variables		
Life	Ratio of gross premiums written in life business to total gross premiums written.	A.M. Best Company, ORBIS, Annual Reports
reinsurance	Ratio of premiums assumed in active reinsurance to total gross premiums written.	A.M. Best Company, ORBIS
Total assets	An insurer's total assets.	ORBIS, Worldscope (WC02999)
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity.	Worldscope (WC02999, WC03501)
Debt	Ratio of total debt to total equity (in book values).	Worldscope (WC03501, WC03255)
Market-to-Book	Ratio of market value equity to book value equity.	Worldscope (WC07210, WC03501)
RoE	Return on equity per share.	Worldscope (WC08372)
Stocks	Average fraction of equity investments to total investments.	A.M. Best Company, ORBIS

Table 13: Variable definitions and data sources used in the empirical study.

Data was retrieved from *Thomson Reuters Financial Datastream*, *Thomson Worldscope*, *ORBIS Insurance Focus* and *A.M. Best Company*.

	$\bar{\psi}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta CoVaR^{\leq}$ (FIN)	$-\Delta CoVaR^{\leq}$ (AMC)	Life	Log.Total.Assets	Market.to.Book	RoE	Leverage	Debt	Non-core Activities	Stocks
$\bar{\psi}$ (AMC)	-0.02											
$-\Delta CoVaR^{\leq}$ (FIN)	0.65	-0.21										
$-\Delta CoVaR^{\leq}$ (AMC)	0.23	0.73	-0.06									
Life	0.04	0.34	0.17	0.33								
Log.Total.Assets	0.02	-0.29	0.18	-0.18	0.50							
Market.to.Book	-0.11	0.32	-0.20	0.36	-0.18	-0.03						
RoE	-0.20	0.30	-0.15	0.33	0	0.12	0.24					
Leverage	-0.06	-0.23	0.12	-0.25	0.56	0.4	-0.49	-0.30				
Debt	-0.08	0.35	0.01	0.44	0.19	0.26	0.04	-0.26	0.37			
Non-core Activities	0.13	0.48	0.10	0.53	0.39	0.25	-0.01	0.04	0.21	0.13		
Stocks	-0.17	-0.32	-0.28	-0.04	-0.28	-0.20	0.25	0.13	-0.23	-0.13	-0.21	
Reinsurance	0	0.46	0.05	0.48	0.11	-0.03	-0.11	0.15	-0.18	-0.07	-0.03	-0.04

Table 14: Correlation between dependent and independent variables in our sample.

B.3 Regressions

	Dependent variable:			
	$\log(\bar{\psi})$ (FIN)	$\exp(-\Delta\text{CoVaR}^{\leq})$ (FIN)	$\log(\bar{\psi})$ (AMC)	$\exp(-\Delta\text{CoVaR}^{\leq})$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	0.857***	0.016***	1.014***	0.034***
	(0.117)	(0.002)	(0.117)	(0.004)
Life	−0.924***	−0.016***	−1.051***	−0.035***
	(0.125)	(0.002)	(0.126)	(0.004)
Log.Total.Assets	0.025***	0.002***	0.036***	0.003***
	(0.009)	(0.0002)	(0.009)	(0.0003)
Market.to.Book	−0.038*	−0.001***	−0.061***	−0.003***
	(0.022)	(0.0004)	(0.022)	(0.001)
RoE	−0.254**	−0.002	−0.188*	−0.003
	(0.103)	(0.002)	(0.108)	(0.004)
Leverage	−0.001	−0.0001***	−0.002*	−0.0002***
	(0.001)	(0.00002)	(0.001)	(0.00003)
Constant	0.943***	0.990***	0.775***	0.969***
	(0.185)	(0.003)	(0.185)	(0.006)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1904.2	−3990.8	1918	−3485.7
Observations	525	525	524	524
Akaike Inf. Crit.	1,904.165	-3,990.808	1,918.044	-3,485.657
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15: Robustness OLS Regression (9) for Insurance Business.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and American non-financial sector (AMC).

	Dependent variable:			
	$\log(\bar{\psi})$ (FIN)	$\exp(-\Delta\text{CoVaR}^{\leq})$ (FIN)	$\log(\bar{\psi})$ (AMC)	$\exp(-\Delta\text{CoVaR}^{\leq})$ (AMC)
	(1)	(2)	(3)	(4)
Life^2 (net)	4.421***	1.402**	5.615***	3.184***
	(1.457)	(0.566)	(1.489)	(0.863)
Life (net)	−4.859***	−1.537**	−5.931***	−3.423***
	(1.601)	(0.683)	(1.644)	(1.037)
Log.Total.Assets	0.196**	0.188***	0.255***	0.339***
	(0.094)	(0.033)	(0.093)	(0.057)
Market.to.Book	−0.188	−0.118	−0.281	−0.245
	(0.196)	(0.092)	(0.214)	(0.152)
RoE	−1.048	−0.174	−0.682	−0.355
	(1.741)	(0.291)	(1.717)	(0.561)
Leverage	−0.006	−0.005*	−0.010	−0.020***
	(0.012)	(0.003)	(0.012)	(0.005)
Constant	0.772	−1.258**	−0.180	−3.614***
	(1.645)	(0.509)	(1.646)	(0.948)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1785.6	750.2	1786.6	1204.2
Observations	492	492	491	491
R^2	0.558	0.662	0.554	0.599
Adjusted R^2	0.545	0.652	0.541	0.587
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16: Robustness OLS Regression (9) for Insurance Business with Net Premiums Written.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and American non-financial sector (AMC).

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta\text{CoVaR}^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta\text{CoVaR}^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	1.366	2.403**	2.372*	1.286**
	(1.183)	(1.012)	(1.265)	(0.504)
Life	−1.390	−2.297**	−2.513*	−1.258**
	(1.303)	(1.125)	(1.413)	(0.586)
Log.Total.Assets	0.360***	0.284***	0.395***	0.111***
	(0.074)	(0.063)	(0.081)	(0.037)
Market.to.Book	−0.550***	−0.274	−0.653***	−0.152
	(0.212)	(0.190)	(0.242)	(0.099)
RoE	1.352	−0.609	2.257	−0.480
	(2.320)	(1.752)	(2.646)	(0.963)
Leverage	−0.045***	−0.035***	−0.046***	−0.016**
	(0.016)	(0.013)	(0.016)	(0.008)
Constant	−2.656**	−1.082	−2.917**	1.000
	(1.324)	(1.049)	(1.417)	(0.622)
Akaike Inf. Crit	198.6	166.9	212.5	87.2
Observations	71	71	70	70
R^2	0.356	0.374	0.346	0.271
Adjusted R^2	0.295	0.315	0.284	0.201
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 17: Robustness OLS Regression for Insurance Business within 2015.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and American non-financial sector (AMC), respectively. Measures are estimated using the years 2009 to 2015, explanatory variables are from 2014. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta\text{CoVaR}^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta\text{CoVaR}^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	3.451^{**}	1.111^{**}	3.562^{**}	1.170
	(1.625)	(0.499)	(1.712)	(0.949)
Premiums.Life	-3.764^{**}	-1.011^{*}	-3.732^{**}	-1.254
	(1.802)	(0.605)	(1.896)	(1.109)
Continent:AFRICA	-1.411^{***}	-1.057^{***}	-1.620^{***}	-1.044^{***}
	(0.355)	(0.170)	(0.347)	(0.322)
Continent:ASIA	-0.314	-0.476^{**}	-0.294	-0.462^{*}
	(0.449)	(0.229)	(0.500)	(0.245)
Continent:AUSTRALIA	-1.188^{***}	-0.503^{***}	-1.108^{***}	-1.451^{***}
	(0.312)	(0.105)	(0.336)	(0.226)
Continent:JAPAN	-0.764^{**}	-0.347^{***}	-0.914^{**}	-1.059^{***}
	(0.371)	(0.086)	(0.388)	(0.235)
Continent:NORTH AMERICA	0.251	-0.009	0.575^{*}	0.638^{***}
	(0.307)	(0.099)	(0.323)	(0.211)
Log.Total.Assets	0.121	0.118^{***}	0.156	0.236^{***}
	(0.112)	(0.030)	(0.112)	(0.050)
Market.to.Book	-0.022	-0.014	-0.074	-0.062
	(0.172)	(0.068)	(0.179)	(0.102)
RoE	-1.022	-0.155	-0.509	-0.027
	(1.582)	(0.290)	(1.547)	(0.478)
Leverage	-0.007	-0.007	-0.007	-0.014^{***}
	(0.015)	(0.004)	(0.015)	(0.005)
Constant	1.588	-0.281	0.668	-2.748^{***}
	(1.858)	(0.491)	(1.877)	(0.784)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1885.7	711.9	1877.9	1125.5
Observations	525	525	524	524
R^2	0.579	0.713	0.586	0.702
Adjusted R^2	0.563	0.703	0.570	0.691
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: Robustness OLS Regression for Insurance Business with continent-fixed Effects.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and American non-financial sector (AMC), respectively. The reference continent is Europe. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta\text{CoVaR}^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta\text{CoVaR}^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	4.363***	1.423**	5.445***	3.187***
	(1.532)	(0.583)	(1.552)	(0.872)
Life	−4.644***	−1.457**	−5.583***	−3.222***
	(1.700)	(0.699)	(1.731)	(1.053)
Non.PH.Liab	0.007	0.003	0.006	0.004*
	(0.008)	(0.002)	(0.008)	(0.002)
Log.Total.Assets	0.174*	0.173***	0.231**	0.307***
	(0.094)	(0.033)	(0.095)	(0.058)
Market.to.Book	−0.266	−0.154	−0.368*	−0.322**
	(0.201)	(0.096)	(0.220)	(0.159)
RoE	−1.608	−0.287	−1.255	−0.461
	(1.435)	(0.304)	(1.420)	(0.555)
Leverage	−0.016	−0.011**	−0.019	−0.025***
	(0.022)	(0.005)	(0.021)	(0.007)
Constant	1.416	−0.915*	0.516	−2.925***
	(1.624)	(0.514)	(1.650)	(0.951)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1887.7	807.7	1898.6	1291
Observations	522	522	521	521
R^2	0.561	0.650	0.552	0.582
Adjusted R^2	0.548	0.639	0.539	0.569
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 19: Robustness OLS Regression for Insurance Business with non-core Activities.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and American non-financial sector (AMC), respectively. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta\text{CoVaR}^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta\text{CoVaR}^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	2.900**	0.976*	3.937***	2.561***
	(1.413)	(0.529)	(1.427)	(0.882)
Life	−2.864*	−0.934	−3.679**	−2.299**
	(1.514)	(0.598)	(1.553)	(1.049)
Stocks	−2.287	−1.542	−2.443	−0.426
	(2.558)	(1.163)	(2.638)	(2.027)
Log.Total.Assets	0.177**	0.166***	0.226***	0.297***
	(0.089)	(0.027)	(0.087)	(0.051)
Market.to.Book	−0.145	−0.057	−0.209	−0.236
	(0.224)	(0.105)	(0.236)	(0.173)
RoE	−1.828	−0.227	−1.400	−0.466
	(1.165)	(0.247)	(1.172)	(0.527)
Leverage	−0.039**	−0.014**	−0.040**	−0.030***
	(0.018)	(0.006)	(0.018)	(0.007)
Life:Stocks	−4.422	−1.910	−5.946	−4.613*
	(3.569)	(1.699)	(3.749)	(2.795)
Constant	1.409	−0.852**	0.569	−2.885***
	(1.557)	(0.420)	(1.536)	(0.875)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1791.9	711.7	1793.8	1222.2
Observations	510	510	509	509
R^2	0.597	0.701	0.598	0.614
Adjusted R^2	0.584	0.691	0.585	0.601
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 20: OLS Regression (12) with Stock Investments.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and the American non-financial sector, respectively. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta\text{CoVaR}^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta\text{CoVaR}^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	4.103***	1.561**	5.425***	3.315***
	(1.521)	(0.643)	(1.578)	(0.937)
Life	−4.434***	−1.544**	−5.538***	−3.380***
	(1.642)	(0.723)	(1.711)	(1.085)
Total.Debt	0.209	0.226	0.400	0.052
	(0.357)	(0.175)	(0.372)	(0.242)
Log.Total.Assets	0.186**	0.172***	0.240***	0.305***
	(0.092)	(0.032)	(0.093)	(0.058)
Market.to.Book	−0.297	−0.179*	−0.412*	−0.306*
	(0.194)	(0.092)	(0.213)	(0.157)
RoE	−1.131	−0.056	−0.576	−0.229
	(1.644)	(0.395)	(1.620)	(0.684)
Leverage	−0.026	−0.012**	−0.026	−0.020**
	(0.019)	(0.006)	(0.020)	(0.009)
Life:Debt	−0.021	−0.176	−0.263	−0.068
	(0.392)	(0.181)	(0.409)	(0.245)
Constant	1.114	−0.971*	0.216	−2.941***
	(1.626)	(0.497)	(1.642)	(0.958)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1903	804.8	1918.1	1305.8
Observations	525	525	524	524
R^2	0.560	0.654	0.547	0.575
Adjusted R^2	0.546	0.643	0.533	0.562
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: OLS Regression (14) with Debt-to-Equity Ratio.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and the American non-financial sector, respectively. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta\text{CoVaR}^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta\text{CoVaR}^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Reinsurance^2	2.065	0.568	2.206	-0.447
	(2.609)	(0.946)	(2.886)	(1.741)
Reinsurance.assumed	-2.159	-0.536	-2.292	0.446
	(2.498)	(0.888)	(2.657)	(1.605)
Log.Total.Assets	0.290^{**}	0.133^{***}	0.343^{***}	0.282^{***}
	(0.124)	(0.031)	(0.123)	(0.067)
Market.to.Book	-0.537^{*}	-0.120	-0.736^{**}	-0.560^{***}
	(0.301)	(0.088)	(0.335)	(0.204)
RoE	-3.122^{***}	-0.361	-2.951^{***}	-1.354^{***}
	(1.074)	(0.229)	(0.994)	(0.334)
Leverage	-0.073^{***}	-0.012^{*}	-0.079^{***}	-0.040^{***}
	(0.026)	(0.007)	(0.025)	(0.009)
Constant	-0.045	-0.317	-0.765	-2.120^{*}
	(2.202)	(0.526)	(2.198)	(1.181)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1902.7	805.5	1918	1302.3
Observations	319	319	319	319
R^2	0.492	0.622	0.469	0.537
Adjusted R^2	0.468	0.605	0.444	0.516
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 22: OLS Regression (15) for Active Reinsurance Business.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and the American non-financial sector (AMC), respectively. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta\text{CoVaR}^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta\text{CoVaR}^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	4.428**	0.703	5.695***	2.513**
	(2.032)	(0.737)	(2.016)	(1.103)
Life	−3.578	−0.451	−4.848**	−2.097
	(2.331)	(0.921)	(2.332)	(1.382)
Reinsurance	0.170	0.018	−0.069	0.472
	(0.923)	(0.260)	(1.007)	(0.631)
Log.Total.Assets	0.308**	0.127***	0.384***	0.306***
	(0.131)	(0.040)	(0.123)	(0.065)
Market.to.Book	−0.567*	−0.130	−0.770**	−0.595***
	(0.343)	(0.092)	(0.386)	(0.191)
RoE	−2.913***	−0.352	−2.626**	−1.225***
	(1.118)	(0.281)	(1.044)	(0.378)
Leverage	−0.072***	−0.014**	−0.075***	−0.041***
	(0.019)	(0.007)	(0.019)	(0.008)
Life:Reinsurance	−0.600	−0.069	−0.066	−0.741
	(1.049)	(0.300)	(1.082)	(0.630)
Constant	−0.399	−0.223	−1.531	−2.487**
	(2.240)	(0.668)	(2.103)	(1.089)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	1196.8	459.7	1192.1	778.8
Observations	319	319	319	319
R^2	0.538	0.636	0.544	0.586
Adjusted R^2	0.514	0.616	0.519	0.564
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 23: Baseline OLS Regression (17) for Primary Insurance and Active Reinsurance Business.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP and the dependence-consistent $\Delta\text{CoVaR}^{\leq}$ with respect to the global financial sector (FIN) and American non-financial sector (AMC), respectively. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:					
	RoA		RoE			
	(1)	(2)	(3)	(4)	(5)	(6)
Life^2	3.299***	5.355***	−8.761*	−3.548		
	(0.858)	(1.533)	(5.120)	(6.117)		
Life	−3.731***	−6.306***	12.141**	4.773	2.959*	1.085
	(1.183)	(1.565)	(5.655)	(6.462)	(1.626)	(1.225)
Log.Total.Assets	−0.327**	−0.212*	−0.196	0.239	−0.102	0.326
	(0.159)	(0.117)	(0.365)	(0.446)	(0.370)	(0.388)
Leverage	−0.059***	−0.039***	−0.392***	−0.230**	−0.353***	−0.227**
	(0.016)	(0.014)	(0.084)	(0.092)	(0.078)	(0.093)
Market.to.Book		0.556**		4.760***		4.703***
		(0.222)		(0.791)		(0.801)
Non.PH.Liab		0.302		−0.149		−0.206
		(0.298)		(0.632)		(0.626)
Constant	9.280***	7.882***	20.004***	6.589	18.686***	5.833
	(2.678)	(2.635)	(6.459)	(7.039)	(6.675)	(6.842)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Continent Fixed Effects		*Y*		*Y*		*Y*
Akaike Inf. Crit	3275.4	3275.4	3275.4	3275.4	3275.4	3275.4
Observations	511	511	511	511	511	511
R^2	0.383	0.508	0.315	0.461	0.303	0.460
Adjusted R^2	0.368	0.489	0.299	0.440	0.288	0.440
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 24: OLS Regression of Insurance Holdings' Profitability.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the return on assets (RoA) and return on equity (RoE) of insurance holdings in our baseline sample, respectively. Robust standard errors are clustered by insurers and provided in parentheses.

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