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Financial Contagion and Diversification of Insurance Activities*

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Abstract

Insurance companies are important counterparties in numerous financial transactions and thus might contribute to financial contagion. Since the core insurance activities, life and non-life business, naturally exhibit a low degree of correlation, they enable diversification of business activities. We motivate the impact of this diversification effect on financial contagion both theoretically and empirically. Our results imply that, on average, a fraction of roughly 60% life business minimizes contagion risk. This fraction tends to increase with an insurer's investment volatility, leverage ratio, and the scope of active reinsurance assumed. We argue that business diversification effects are more pronounced for insurers compared to banks since different insurance claims are loosely correlated. Our findings have important implications for the design of macro-prudential policies.

Keywords: Financial Institutions, Financial Contagion, Diversification

JEL Classification: G01, G22, G23, G28

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1 Introduction

Insurance companies conduct numerous different business activities, e.g. selling insurance, managing assets, providing loans, or lending assets. In this article we study their core business activity, namely ensuring insurance protection to policyholders, and its relation to financial contagion, i.e. the propensity to generate or amplify the spill-over of economic shocks to other financial institutions. Insurance 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 insurance activities is substantial. For example, U.S. insurance companies have 45% of the United State's GDP in assets under management (Bureau of Economic Analysis (bea) (2017)).[1] Total insurance premiums written in the United States have a volume of almost one tenth of total loans outstanding in the U.S.[2]

When housing prices collapsed in 2008, one of the largest insurers in the United States, the American International Group (AIG), lost approximately 21 billion USD from securities lending activities (McDonald and Paulson (2015)). These losses occurred as AIG invested collateral from its security lending business into risky assets, particularly residential mortgage-backed securities (RMBS), asset-backed securities (ABS), and collateralized debt obligations (CDO). Upon the announcement of substantial losses on these investments in August 2008, counterparties tried to reduce their exposure to AIG by requesting a return of their cash collateral. However, due to the substantial losses on the invested collateral, AIG was not able to meet the collateral calls. Since policymakers feared that the losses of AIG might spill over to its counterparties and, thereby, amplify the financial crisis, they received a government bailout. These events initiated a controversial debate about the relation between insurance companies and systemic risk (e.g. Billio et al. (2012), Kessler (2013), Cummins and Weiss (2014), Thimann (2014)).

The near-default of AIG triggered two main hypotheses about the systemic risk of insurance

[1] 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)).

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

activities: I) On the one hand, several authors argue that primarily non-core insurance activities[3] as securities lending, but not core insurance activities 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 contagion risk measures that capture systemic risk from a financial market's perspective suggest that life insurance companies contribute to a much larger extent to systemic risk than non-life insurers (e.g. Berdin and Sottocornola (2015), Kaserer and Klein (2017), International Monetary Fund (2016)).[4] A common explanation that combines the two hypotheses is that life insurance companies engage more in non-core insurance activities (Cummins and Weiss (2014)).[5] Additional explanations include that, due to their size, life insurers contribute more than non-life insurers to asset comovements via similar 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 different insurance activities relate to systemic risk.

In this article, we develop a novel rationale for the effect of core insurance activities on financial contagion. The main insight from our study is that diversification across insurance activities relates to economies of scope that are beneficial for financial contagion. First, 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 French insurance group AXA, according to premiums written one of the largest insurance holdings worldwide, is classified by its first SIC code (6311) as life insurer.[7] However, it has on average underwritten only 65% of gross premiums in life insurance and 35% in non-life insurance from 2006 to 2014. Thus, classifying AXA as life insurer leads to a profound misjudgment of AXA's business activities. The same issue appears with the largest insurer according to total assets, Allianz Group,

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

[4] Popular contagion 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.

[6] Note that most popular contagion 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] For example, Weiß and Mühlnickel (2014) and Bierth et al. (2015) split their sample into life and non-life insurance companies by using SIC codes.

which is classified as life insurer according to its first SIC code as well, but has only underwritten roughly 35% of gross premiums in life insurance during 2006 to 2014. By studying an insurance holding's actual fraction of life business in a panel regression of contagion risk measures, we find that more life insurance does not necessarily increase contagion risk. In contrast to above hypothesis II), underwriting more life insurance can actually decrease an insurance holding's contagion risk if the current fraction of life business is low. This finding implies that the systemic risk related to non-life insurance activities has been understated in previous studies (for example in Cummins and Weiss (2014), Bierth et al. (2015) or International Monetary Fund (2016)).

Second, in a simplified model in Section 2 we show that diversification across different business activities can reduce contagion risk of multiline companies in comparison to monoliners. For this purpose, we focus on credit risk as an exemplary channel for financial contagion that potentially results 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 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 equal to or larger than 50%. This result is illustrated in Figure 1: If the insurance holding underwrites either more or less life business than at credit-risk minimizing fraction (which equals 50% in this example), the counterparty's expected loss increases. The credit-risk minimizing fraction of life business tends to increase with the insurance holding's leverage ratio as given by total assets over equity. The main driver of our results is a low correlation between life and non-life insurance activities that enables diversification of cash flows.

In Section 3 we confirm these predictions with respect to financial contagion in general. For this purpose, we examine empirical contagion risk measures in a panel regression with 75 international insurance companies between 2007 and 2015. Our main finding is that, on average, a fraction of roughly 60% of life business minimizes contagion risk. The contagion risk of insurers with a smaller fraction of life business is decreasing if they replace part of their non-life business with life business. However, a large fraction of life business can, instead, increase contagion risk. Changes in the fraction of life business are economically important: At the fraction of life business that minimizes contagion risk, an increase or decrease by one standard deviation of the fraction of life business is related to an increase of 8% to 30% in contagion risk. Therefore, in contrast to hypothesis I),

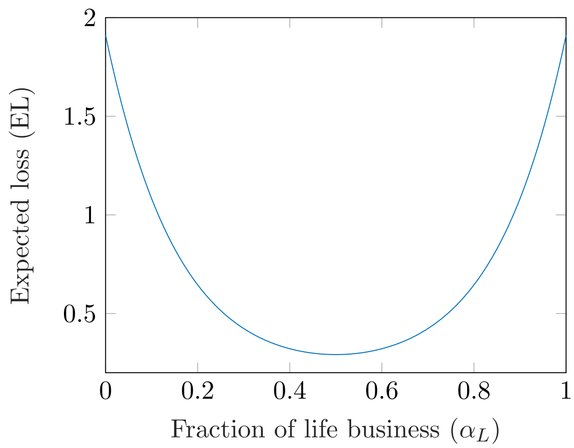


Figure 1: Expected loss of a counterparty that holds a claim to an insurance holding. In this example, we assume that life and non-life business returns are independent but come from the same distribution.

core life and non-life business can indeed have a profound impact on systemic risk, although it might arise in the context of non-core insurance activities (as issuing subordinated debt or lending securities).

A diversification effect between life and non-life insurance business is indeed recognized by micro-prudential regulation, as the European Union's regulatory regime for insurers, Solvency II, explicitly assumes risk mitigation between life and non-life insurance business (European Commission (2015)): Since the calculation of the solvency capital requirement (SCR) assumes zero correlation between the SCR for life and non-life, the holding's SCR is smaller than the sum of the individual SCRs for life and non-life business.[8] Confirming this rationale, Berdin et al. (2017) find that EU insurance companies are less exposed to persistently low interest rates if they diversify in insurance activities.

Additionally, we study the impact of active reinsurance business on financial contagion. We do not find a diversification effect between primary insurance and active reinsurance, which is not surprising, since cash flows from these two activities are highly correlated. However, reinsurance business usually exhibits a higher volatility than primary insurance, as it typically captures the tail risks originating from primary insurance contracts (e.g. in excess-of-loss reinsurance agreements). In an empirical analysis we show that more reinsurance business tends to increase the diversification benefit of life insurance. A larger share of reinsurance business increases the contagion-risk

[8]The total SCR of the insurance holding is then given as $\sqrt{SCR_{life}^2 + SCR_{non-life}^2}$ which is smaller than $SCR_{life} + SCR_{non-life}$.

minimizing fraction of life business. This finding suggests that the positive effect of a low volatility and high expected life business cash flows partly compensates the negative effect of a relatively higher tail risk of reinsurance business. Nevertheless, we find that the effect of reinsurance as well as an insurer's leverage or investment volatility on diversification between life and non-life business is insignificant. This supports the view that diversification is primarily caused by a low degree of correlation between life and non-life cash flows.

We find that diversification between life and non-life business can reduce financial contagion. Does this finding imply that all insurance companies should exploit this diversification in order to increase financial stability? Wagner (2010) argues that a higher degree of diversification across many financial institutions also raises the homogeneity along business activities. 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.

In Section 4 we argue that diversification of insurance activities does not necessarily come with a larger correlation of exposures within the insurance sector. While diversification across assets might indeed imply the investment into a similar portfolio, diversification across insurance activities does not imply the underwriting of the same risk. Instead, policyholders typically hold only one insurance policy for a specific risk, for instance car liability insurance. In property and casualty insurance, in particular, insurers usually prohibit insuring the same risk with a second insurer. Since typical insurance claims, e.g. from motor or homeowners' insurance, are independent across policies, the exposure of insurers exhibits a small degree of correlation. Nevertheless, this argument does not necessarily apply to catastrophic events that simultaneously affect a large number of insureds at different insurers, like storms or earthquakes. Eventually, the overall effect of diversification of insurance activities can increase financial stability if its benefits outweigh the effect of correlated exposures, e.g. from catastrophic events.

Nonetheless, diversification does not necessarily increase profitability of insurers. In contrast, we find that multiline insurers exhibit a smaller return on assets and return on equity than monoline insurers. We argue that this finding reflects a trade off between economies of scope and economies of scale: The less diversified an insurer's insurance activities are, the more policies it underwrites in a particular line of insurance. A large number of policies 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 activities, which, for a given size of the insurer, decreases the number of contracts within one 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. Hence, insurance holdings might face high incentives to exploit economies of scale to increase profitability in contrast to exploiting economies of scope that could lower contagion risk.

Our analysis builds on previous work on the impact of 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. This is because, upon the risk transfer, insurers invest in the same asset as banks. As insurers face a shock, they liquidate the asset, which depresses its price and causes losses of banks. Similarly, in 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 homogenous.

We extend this literature in two ways: First, we do not consider diversification in terms of asset investments but in terms of business activities. The important distinction to the previous literature is that insurers are able to diversify across insurance activities without necessarily increasing the correlation of exposures across insurers. Particularly due to insurers preventing insureds from insuring the same risk at different insurers, claim payments for non-catastrophic events exhibit a small correlation across insurers. Therefore, the intuition of previous studies finding that diversification is related to correlated exposures and increases systemic risk does not necessarily hold in the insurance case. Second, we extend the previous studies by providing empirical evidence that diversification along (uncorrelated) insurance activities indeed reduces financial contagion.

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 or 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 find empirical evidence that multiline insurers indeed exhibit a smaller return on assets and return on equity than monoline insurers, which is consistent with previous studies that find diversification not to benefit the profitability of banks.

Finally, we extend previous empirical studies on the determinants of insurance companies' contribution to financial contagion. We differ from these studies in two 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 the risk of financial contagion 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 contagion risk and find it to be positive. We contrast these studies by finding a significant non-linear effect of life insurance on financial contagion such that contagion risk for non-life insurers decreases with increasing life insurance activities. Second, we distinguish between financial contagion 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 contagion. As Kubitza and Gründl (2017) show, the effect of financial contagion can be very persistent, particularly during crises. Thus, measures for the short-term contribution to financial contagion might underestimate the actual contagion risk of financial institutions.

2 Diversification and Counterparty Credit Risk

In the following, we examine the impact of insurance business activities with respect to counterparty credit risk as one exemplary channel for contagion risk. This channel exists, for example, if an insurance holding has issued subordinated debt to a counterparty:[9] If the insurance holding's profit and loss (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. The same rationale holds for other financial linkages, e.g., stemming from derivatives trading or securities lending.[10]

2.1 Model

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-interest income of banks. The model serves two purposes: First, the portfolio view provides a straightforward identification and interpretation of diversification effects between life and non-life business. The main intuition is that the low degree of correlation between life and non-life insurance claims can reduce the total profit and loss volatility of diversified insurance holdings and, thereby, the expected credit exposure of a counterparty. Second, the model enables us to derive comparative statics about the credit-risk minimizing fraction of life business, i.e. the optimal degree of diversification. Based on these comparative statics, we derive testable hypotheses for the subsequent empirical analysis in Section 3.

Initially, at time $t = 0$ the insurance holding is equipped with an initial amount of capital (equity) and a second liability position, namely a claim of size D that is due at time $t = 1$ to another counterparty. The holding's total funds are, without loss of generality, scaled to one unit, and are invested at time $t = 0$ into life and non-life insurance operating companies which sell life and non-life insurance contracts, respectively. The holding invests an 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 the holding owns the major share of both operating companies, such that these are

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

[10]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)).

consolidated at the holding level.[11] We call the operating companies *subsidiaries* from here on. At time $t = 1$, the insurance holding receives $\alpha_L R_L$ and $(1 - \alpha_L)R_{NL}$ of the subsidiaries' profits, respectively, where R_L and R_{NL} denote the subsidiaries' gross return on equity.

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[12], asset returns, and the growth of insurance reserves for old and new contracts.

The subsidiaries' return on equity is based on the ultimate cash flow that remains after investment returns have realized, policyholder claims are served and insurance reserves of newly sold contracts are allocated. This return can be employed by the holding to serve the counterparty's claim. The consolidated profit of the insurance holding is given by

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

where $\alpha_L \in [0, 1]$ is the capital invested in the life insurance company. For simplicity, we assume that returns are normally distributed.[13]

The insurance holding has engaged in a financial transaction that obligates it to serve a claim D to a counterparty at time $t = 1$. For instance, D might be an interest (or principal) payment for subordinated debt or a collateral call resulting from securities lending transactions. The repayment of the claim is endangered in case the holding's profits (resulting from the subsidiaries' business) are 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)). Note that, in

[11] 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.

[12] For example, term life insurance policies involve a periodically (typically annually 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.

[13] This distributional assumption is made for the sake of simplicity. 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.

our model, the counterparty claim might as well result from a transaction undertaken by one of the subsidiaries that is backed by a guarantee of the holding company.

If the subsidiaries' profits are sufficiently large, the resulting return to the holding covers the counterparty's claim. Otherwise, the holding might employ (part of) its equity capital to pay the claim. As we assume that the holding controls the major share of the subsidiaries' business, the holding's equity capital results from consolidation of the subsidiaries' equity. Figure 2 illustrates the stylized consolidated balance sheets of the insurance holding and the counterparty.

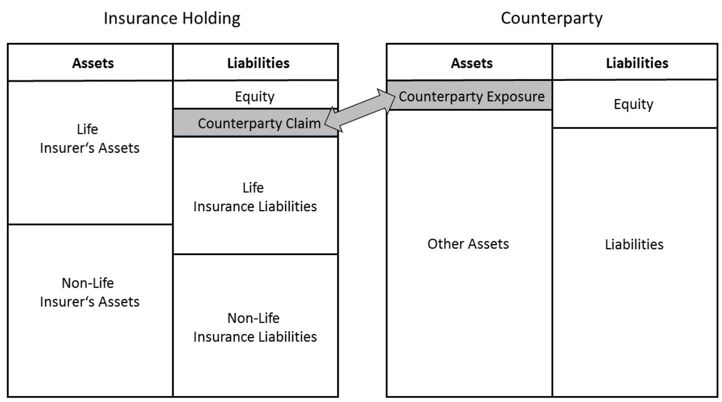


Figure 2: Illustration of the simplified consolidated balance sheets of the stylized insurance holding and counterparty.

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

$$
\begin{aligned}
EL &= D - \mathbb{E}\left[\min\left(D, C + R\right)\right] &(2)\\
&= (D - \mu)\Phi\left(\frac{D-\mu}{\sigma}\right) + \sigma\varphi\left(\frac{D-\mu}{\sigma}\right), &(3)
\end{aligned}
$$

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 sum of the insurance holding's equity capital and (consolidated) profit at time $t = 1$, $C + R$.

EL reflects the value of a put option at strike D on the holding's profit and equity: If the latter is large enough, the loss is zero, and vice versa. This equivalence implies that the expected loss is increasing with the profit's volatility. The latter is given as

$$\sigma^2 = \alpha_L^2\sigma_L^2 + (1-\alpha_L)^2\sigma_{NL}^2 + 2\alpha_L(1-\alpha_L)\sigma_L\sigma_{NL}\rho, \tag{4}$$

where ρ is the correlation between life and non-life free cash flows stemming from the operating insurance companies. The investment cash flows of these companies are in particular likely to be positively correlated, as investments might overlap or be positively correlated. 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 expect 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) profit 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*

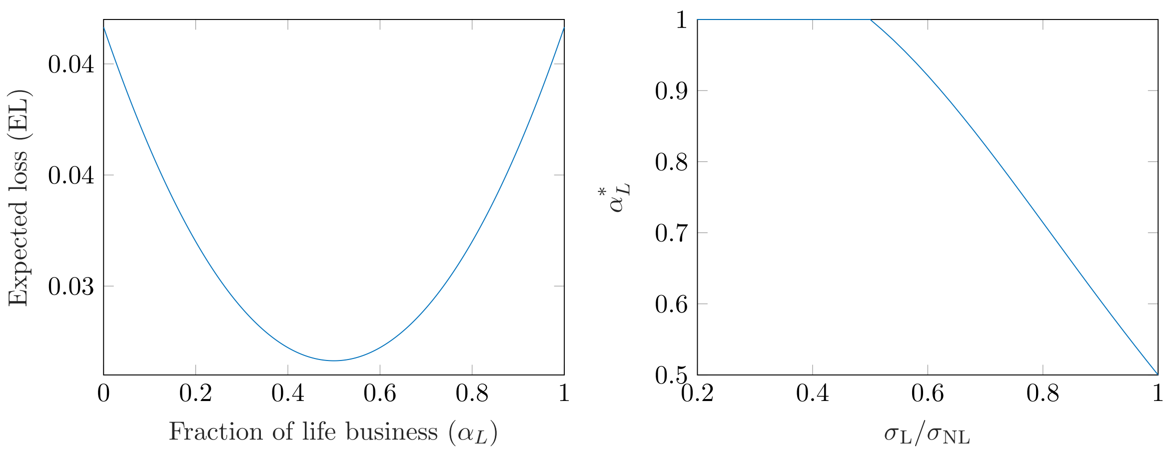
$$\alpha_L^* = \frac{\sigma_{NL}^2 - \sigma_L\sigma_{NL}\rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho}. \tag{5}$$

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 volatility of the life (non-life) business, if* ρ *is sufficiently small.*

Proof: See Appendix A.

Figure 3 illustrates the results from Lemma 1. First, Figure 3 (a) shows that the expected loss is u-shaped in the fraction of life business. This implies the existence of a minimum, i.e. a credit-risk minimizing fraction of life business α_L^*. An increase or decrease in the fraction of life business leads to an increase in credit risk since then shocks from one business activity can be diversified less efficiently. As the expected returns from life and non-life business are equal, α_L^* is the fraction of life business to achieve a minimum variance portfolio of the holding company.

Second, Figure 3 (b) depicts the credit-risk minimizing fraction of life business α_L^* with respect to the return volatility. 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, a smaller fraction of life business minimizes credit risk.[14]



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

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

Figure 3: 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 $capital = 1$.

In the following we provide empirical evidence that suggests that cash flows from the life subsidiary are less volatile than from the non-life subsidiary. For this purpose, we distinguish between insurance and investment activities. 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 (Cummins and Weiss (2016)) and a larger volatility than cash flows in life insurance.

The typical duration of non-life contracts is one year. Thereafter, contracts and premiums can be altered by the insurer 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))

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

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 annual growth rates of the underwriting profit and loss statements of insurance companies. In Table 1 we report the mean and volatility of underwriting growth rates in life & health (L&H) as well as property & casualty (P&C) insurance business of U.S. insurance holding companies. The data is based on observations from 2006 and 2016 as provided by A.M. Best Company. The growth rates generated by P&C insurance business are indeed substantially more volatile than that resulting from L&H business. Moreover, the mean growth rate in L&H insurance business is substantially larger (26%) than that in P&C insurance (-56%).[15] In line with these results, Kahane and Nye (1975) also find a negative rate of return in the P&C insurance industry. One possible reason for this result can be a higher degree of competition in P&C than in L&H insurance, such that insurers are more reluctant to take high premium loadings for P&C than for L&H insurance products (Cummins et al. (1999)).

	Life & Health Cash Flow	Property & Casualty Cash Flow
Mean Growth Rate	0.26	-0.56
Volatility of Growth Rate	5.16	37.25

Table 1: Underwriting Growth Rate: Mean and volatility.
The sample consists of 1642 insurer-year observations from consolidated income statements of 228 U.S. insurance companies during 2006 to 2016. We excluded observations with zero underwriting profit. *Mean Growth Rate* is the average growth rate of an insurance company's annual underwriting profit across all insurer-year observations. *Volatility of Growth Rate* denotes average growth rate of an insurance company's annual underwriting profit across all insurer-year observations. Growth rates are calculated for life & health and property & casualty business separately. Source: *A.M. Best Company, Own calculations.*

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. life and non-life (property & casualty) insurers' investment portfolio for exemplary asset classes. In 2016, the average U.S. life insurer held roughly 72% of total financial assets in bonds, while it was 55% for the average non-life insurer. The massive bond portfolios of life insurers typically consist of long-term bonds that are held to maturity in order to reduce the duration gap between assets and liabilities (Thimann (2014)).[16] Thus, cash flows from insurers'

[15] Note that a negative growth rate in underwriting profit can be compensated by returns from investment activities.

[16] 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.

bond investments are relatively stable over time. Moreover, Table 2 shows that life 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, non-life 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 the average primary German life (non-life) insurer held 85.9% (75.3%) of financial assets in bonds and debentures, 24.3% (17.5%) in loans and mortgages, and 4.4% (7.3%) in stocks (German Insurance Association (GDV) (2017)).[17]

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.

We conclude that cash flows resulting from asset investment as well as insurance business are less volatile in life insurance than non-life insurance. This conclusion is supported by several empirical studies that 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)). As we show in the following lemma, the resulting smaller volatility of the return from life business implies that it is optimal to underwrite more life than non-life insurance business in order to minimize credit risk, everything else being equal. This finding is consistent with the evolution of α_L^* in Figure 3 (b).

Lemma 2. *Assume that the expected returns from life and non-life business do not differ and that their correlation is nonnegative. If the return from life business is less volatile than that from non-life business, the credit-risk minimizing fraction of life business is larger than 50%.*

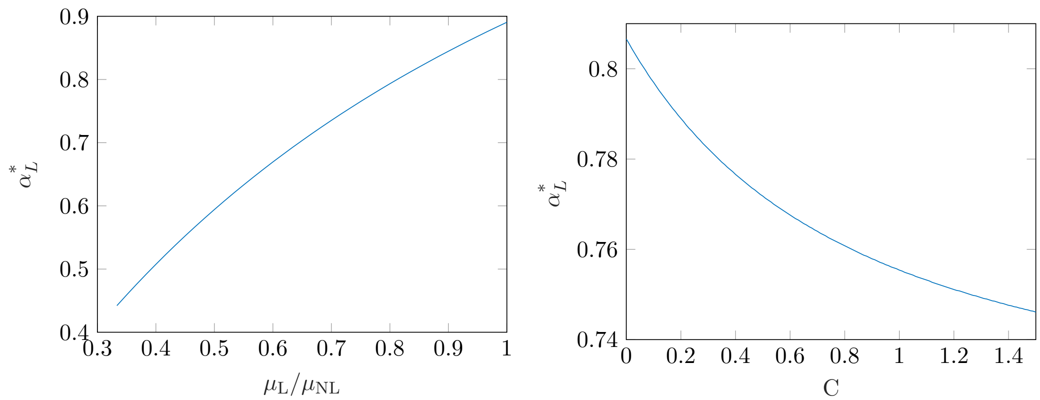
Proof: See Appendix A.

The previous results assume that the expected returns from life and non-life business are equal.

[17]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)).

However, our empirical analysis of underwriting growth rates in Table 2 suggests that the expected return from non-life insurance activities is smaller than that from life insurance activities. Hence, if the non-life subsidiary is not able to generate a substantially larger expected asset return than the life subsidiary, the overall return from life business will be larger than that from non-life business.

Figure 4 (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}.



(a) μ_{NL} vs. μ_L.

(b) $\mu_{NL} = 1.1$.

Figure 4: Fraction of life business α_L^* that minimizes credit risk for the following return characteristics: 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 $C = 1$.

If expected returns from life and non-life business differ, another important characteristic governs the diversification potential between business activities: the size of equity capital C available. The less equity capital the holding has access to, the less likely is the repayment of the counterparty's claim. Instead, the counterparty is more likely receive the holding's random return. Hence, if the 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. The following lemma confirms this intuition.

Lemma 3. *Assume that the return from life business is less volatile and larger in expectation than that from non-life business. If, equity capital is sufficiently small,* $\alpha_L^* = 1$.

Proof: See Appendix A.

Figure 4 (b) illustrates this finding: The smaller the insurer's equity basis, the larger is the fraction of life business that minimizes the expected counterparty loss (α_L^*). Thus, financially distressed non-life insurers contribute more to financial contagion than financially distressed life insurers, everything else (e.g. total size) being equal.

Finally, we consider differences in investment and insurance returns. For this purpose, we split up the subsidiaries' returns into that from insurance and investment activities, $R = \alpha_L R_{INS,L} + (1 - \alpha_L) R_{INS,NL} + R_{INV}$, where R_{INV} is the return from investment activities, and $R_{INS,L}$ and $R_{INS,NL}$ the return from life and non-life insurance activities, respectively. Suppose that the volatility of the investment return increases. As Figure 5 shows, if the expected return from life insurance activities is larger than that from non-life insurance, the credit-risk minimizing fraction of life business is increasing with investment volatility. This suggests that an increase in the investment volatility increases the diversification benefit of life insurance activities. The intuition is similar to that underlying the interaction with equity capital: The less likely the repayment of the full counterparty claim, the more beneficial is a larger expected return.

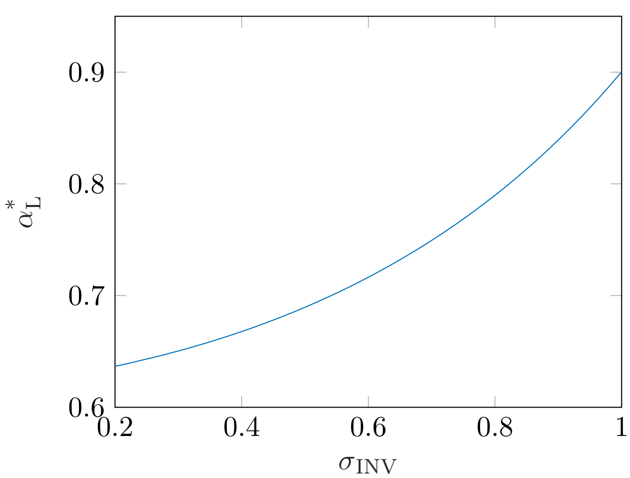


Figure 5: Fraction of life business α_L^* that minimizes credit risk for the following return characteristics: Expected life and non-life insurance return $\mu_{INS,L} = 1.1$ and $\mu_{INS,NL} = 1$, life and non-life insurance return volatility $\sigma_{INS,L} = 0.4$ and $\sigma_{INS,NL} = 0.5$, expected investment return $\mu_{INV} = 1$, insurance and investment return correlation $\rho = 0.5$, claim $D = 0.5$, and equity capital $C = 1$.

2.2 Hypotheses Development

In our theoretical model, we employ counterparty credit risk as one exemplary channel for the transmission of economic shocks. Therefore, the question remains whether the trade off between life and non-life business exists to the same extent with regard to financial contagion in general. To answer this question, we will turn our attention to empirical measures for contagion risk in the following section. The previous analysis implies the following hypotheses by transferring our previous results about credit risk to contagion risk:

Particularly Figure 3 suggests that contagion risk is u-shaped with respect to the fraction of life business: Since life and non-life insurance business are not perfectly correlated, multiline insurance companies might pose a smaller credit risk than monoliners:

(H1): The relationship between contagion risk and an insurance holding's fraction of life business is u-shaped, i.e. contagion risk is decreasing for a small fraction of life business and increasing for a large fraction of life business.

Life insurance is usually associated with a less volatile cash flow than non-life insurance, which implies that, in order to minimize credit risk, it is optimal to underwrite more life than non-life insurance if life and non-life expected returns are similar (Lemma 2):

(H2): The contagion-risk minimizing fraction of life business is larger than 50%.

Figure 4 (c) suggests that an increase in investment volatility is accompanied by an increase in the credit-risk minimizing fraction of life insurance:

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

Lemma 3 suggests that less equity capital implies a higher credit-risk minimizing fraction of life business. As the total size of liabilities is fixed in our model, less equity capital implies a higher leverage ratio, as given by total assets over equity. Hence, our findings imply the following hypothesis:

(H4): The larger an insurance holding's leverage ratio, the larger is the contagion-risk minimiz-

ing fraction of life business.

Moreover, from our model we can also derive an intuition about the relation between contagion risk and active reinsurance business. First, primary insurance and reinsurance liabilities are strongly (almost positively) correlated - in contrast to life and non-life liabilities. Therefore, we expect the diversification effect between primary insurance and active reinsurance with respect to contagion risk to be much smaller than between life and non-life insurance:

(H5): The relationship between contagion risk and an insurance holding's fraction of reinsurance business assumed is only slightly u-shaped or linear.

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 reinsurance business assumed, the larger is the contagion-risk minimizing fraction of life business.

3 Empirical Analysis of Contagion Risk

The central insight from the previous section is that a non-trivial fraction of life business might minimize credit risk. To test the predictions of the simplified portfolio model, we will proceed by empirically studying measures for contagion risk.

3.1 Contagion Risk Measures

We focus on contagion risk measures for the contribution of an institution to the risk of a system of institutions. The idea of the 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 eventually result in the realization of systemic risks, which gives rise to an alternative name of these measures, namely *systemic risk measures*.

We identify shocks based on the total return index (r^I) of each institution I as it 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 in an index in order to mitigate endogeneity in our results.[18]

As our first measure, we employ an institution's dependence-consistent $\Delta\text{CoVaR}^{\leq}$ that 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

$$\Delta\text{CoVaR}^{\leq}_{S|I}(q) = \text{CoVaR}_{r^I \leq VaR^I(q)}(q) - \text{CoVaR}_{\mu^I - \sigma^I \leq r^I \leq \mu^I + \sigma^I}(q) \tag{6}$$

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

$$\mathbb{P}\left(r^S \leq \text{CoVaR}_{S|I}(q) \mid r^I \leq VaR^I(q)\right) = q, \tag{7}$$

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 financial contagion is measured as the difference in the system's

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

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$^{\leq}$ is an extension of Adrian and Brunnermeier (2016)'s ΔCoVaR methodology. Adrian and Brunnermeier (2016) show that ΔCoVaR$= -\rho^{I,S}\sigma^{I}\Phi^{-1}(q)$ 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, contagion 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 contagion risk measures are capture volatility similarly to the expected credit risk exposure in Section 2. Thus, we expect a similar effect of diversification.

ΔCoVaR is based on the system's Value-at-Risk conditional on the institution being exactly at its Value-at-Risk, CoVaR$_{r^I=VaR^I(q)}$. In contrast, the dependence-consistent ΔCoVaR$^{\leq}$ 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 ΔCoVaR$^{\leq}$ is continuously increasing 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 ΔCoVaR$^{\leq}$ is inversely related to an institution's contribution to contagion risk, we use $-\Delta$CoVaR$^{\leq}$ in the panel regressions, such that a higher value relates to higher risk.

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 contagion risk, such as the ΔCoVaR$^{\leq}$, 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 contagion 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),

$$\psi_\tau^{S|I} = \mathbb{P}\left(r_\tau^S \leq VaR^S(q) \mid r_0^I \leq VaR^I(q)\right). \tag{8}$$

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 contagion. 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,

$$\overline{\psi}_{S|I} = \frac{1}{\tau_{\max}} \int_0^{\tau_{\max}} (\psi_\tau - q) d\tau, \tag{9}$$

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 financial contagion. 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 market 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 rises. In this case, measures such as ΔCoVaR$^{\leq}$ or Average Excess CoSP will reflect the risk of contagion from A to B.

Of course, there exist other measures for contagion risk, from which the most popular are probably 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. In this article we focus on the impact of an insurer's business diversification on the risk that a shock spills over from this insurer to other institutions. Therefore, $\Delta\text{CoVaR}^{\leq}$ and Average Excess CoSP seem more appropriate to use in the empirical study. Nevertheless, in unreported regressions we derive similar empirical results with respect to MES. Indeed, it seems reasonable that diversification between life and non-life risks impacts contagion risk not only in one but also in both directions, i.e. from the insurer towards other institutions as well as from other institutions towards the insurer.

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 $\Delta\text{CoVaR}^{\leq}$ we employ Maximum-Likelihood estimates and a Generalized Linear Model for $\overline{\psi}$ analogously to Kubitza and Gründl (2017).

3.2 Explanatory Variables

The main variable of interest is the fraction of life business within an insurance holding. The theoretical model is based on diversification of cash flows. As insurance premiums are part of an insure's cash flow and reflect the size of invested assets, insurance reserves as well as expected claim payments, we approximate the fraction of life business by gross premiums written in life business relative total gross premiums (*Life*). Note that, in contrast to net premiums written, gross premiums written do not subtract insurance business ceded to reinsurers. We employ gross premiums as a primary variable since it reflects the business size and risk that an insurer undertakes before any risk management or investment decisions such as reinsurance. Nevertheless, we find that our results also hold when measuring the size of life business according to net premiums. 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*).

To proxy the volatility of investment activities, we employ the fraction of an insurance holding's consolidated stock investments relative to total investments. Non-core activities are analogously to Bierth et al. (2015) given 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 contagion 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)).

Since the contagion risk measures we employ are based on equity returns, 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.[19] A high profitability might serve as protection against economic shocks, since it typically increases an institution's solvency margins (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 contagion 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 contagion risk. Hence, it is not surprising that similar studies found an ambiguous effect of these variables on contagion risk (e.g. Weiß and Mühlnickel (2014) and Bierth et al. (2015)).

Another important explanatory variable is an insurer's leverage ratio. In line with our theoretical model, we approximate an insurer's leverage as the book value of assets divided by the book value equity. The empirical evidence on the relation of an insurance company's leverage to financial contagion 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 claim are made) and incorporate a safety margin, an insurer's leverage might not necessarily increase its contribution to contagion risk. Nonetheless, a high leverage ratio reduces 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 highly levered life insurance companies are more vulnerable to shocks and tend to contribute more to contagion risk.

To approximate investment volatility, we calculate the fraction of total equity stock investments

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

relative to total investments insurance holdings. As this investment class is among the most volatile investments of insurers, we expect the investment return volatility to increase with the fraction of stock investments (*Stocks*). We account for changes in the regulatory or market environment by including year fixed effects.

3.3 Data

To compute the contagion 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).[20] 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 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 is 8.4 trillion USD in 2015, which indicates that our index incorporates a very large share of financial institutions.[21] Moreover, we employ the Datastream index for all American non-financial companies (AMC). We describe its composition in Appendix B.1.

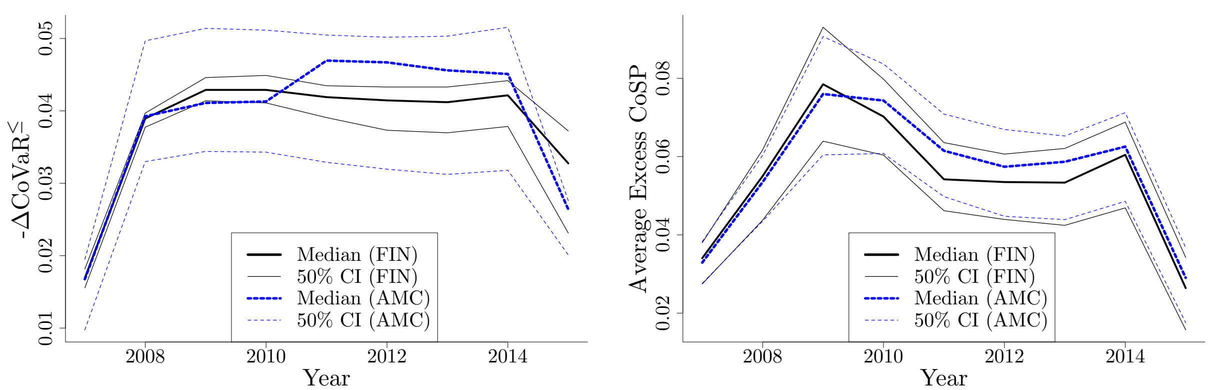
Yearly firm-level data in our baseline sample is retrieved from *A.M. Best Company*, *Thomson Reuters Worldscope*, and *ORBIS insurance focus*. Where available, we employ data from consolidated annual statements provided by *A.M. Best Company*, as this data is most detailed and granular. If not available, 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*. *ORBIS insurance focus* restricts access to firm-level data to 10 years and thus the panel is restricted to the years from

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

[21] 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`).

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 75 insurance companies.[22] This sample is smaller than in comparable studies (e.g. Bierth et al. (2015)), since data, particularly for life premiums written, is very restricted. In order to study the impact of active reinsurance in Section 3.8, 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 6 illustrates the evolution of the contagion 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 financial contagion. The median $-\Delta\text{CoVaR}^{\leq}$ does not decrease until 2015 in Figure 6 (a), while the Average Excess CoSP in Figure 6 (b) signals a decline in contagion risk from 2010 on. Thus, the evolution of $-\Delta\text{CoVaR}^{\leq}$ indicates that short-term contagion risk was high even after the crisis for a long time, while the evolution of the Average Excess CoSP indicates that overall uncertainty and associated long-term contagion risk declined. These differences motivate the use of both measures in the empirical analysis.



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

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

Figure 6: Time evolution of contagion risk measures. The figure shows the median (bold) and 50% confidence interval around the median of the empirical distribution of each contagion 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.

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

Moreover, the measures in Figure 6 also exhibit substantial differences between the financial and non-financial sector. These are particularly large for $-\Delta\text{CoVaR}^{\leq}$, as its volatility across insurance companies in our sample in particular is larger with respect to the non-financial than to the financial sector. Hence, there is a larger discrepancy between the risk insurers might pose for the non-financial sector than for the financial sector, for example since insurers are very differently interconnected with the non-financial sector. These differences motivate us to distinct between contagion risk with respect to the financial and to the non-financial sector.

Descriptive statistics of the contagion risk measures and explanatory variables are reported in Table 3. The mean values of the Average Excess CoSP in our sample are 5.3% and 5.5% with respect to the global financial (FIN) and the American non-financial (AMC) market, respectively. These imply that an average insurer in our sample increases the average likelihood of a sector's shock by 5.3% (FIN) and 5.5% (AMC) 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.

Statistic	N	Min	Max	Median	Mean	St. Dev.
Average Excess CoSP ($\bar{\psi}$) (FIN)	534	0.001	0.118	0.054	0.053	0.022
Average Excess CoSP ($\bar{\psi}$) (AMC)	533	0.001	0.115	0.057	0.055	0.022
- $\Delta\text{CoVaR}^{\leq}$ (FIN)	534	0.008	0.047	0.040	0.037	0.009
- $\Delta\text{CoVaR}^{\leq}$ (AMC)	533	0.004	0.053	0.037	0.037	0.013
Life	534	0.000	1.000	0.438	0.442	0.382
Total Assets (billion USD)	534	1.367	1,562.116	45.889	136.620	221.692
Market-to-Book	534	0.192	4.022	1.138	1.324	0.690
RoE	534	−1.014	0.374	0.106	0.095	0.108
Leverage	534	0.026	49.890	0.145	2.445	4.779
Non-core Activities	531	0.000	440.151	1.286	2.611	19.371
Stocks	519	0.000	0.612	0.045	0.074	0.089
Reinsurance	328	0.000	1.000	0.025	0.163	0.295

Table 3: Descriptive statistics for contagion 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.

The average fraction of life business in our sample is 44.2%, which is very close to the median value (43.8%). 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. This large range of companies and the relatively high standard deviation within our sample (38.2%) allows us to reliably identify the effect of life business on contagion risk.

The average insurer's total assets is roughly 1,562 billion USD, which is substantially larger than the median value of 45.9 billion USD. To account for the skewness of the distribution, we employ the natural logarithm of total assets in the model. 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. Thus, this bias in size is not surprising if we assume that large insurers are more likely to report detailed balance sheet variables. Moreover, the difference in size also explains why insurers in our sample exhibit higher values of contagion risk than in previous studies, as size is typically positively related to contagion risk.

The average insurer in our sample exhibits a market-to-book ratio of 1.32 (with median value 1.14), a return on equity of roughly 9.5% (with median value 10.6%), and a leverage ratio of 2.45 (with median value 0.15). 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 geographical distribution of the 75 insurers' headquarters in our baseline sample is as follows: 45% insurers are based in Europe (the largest proportions are in 8% in Switzerland, 7% in Italy, and 5% in Germany), 38% in North America (31% in the U.S. and 7% in Canada), 8% in Asia, 4% in Africa, 2% in Japan, and 2% in Australia.[23]

The average insurer in our sample invests 7% in stocks, which, however exhibit a large dispersion between 0% and 61% of stock investments. Moreover, 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. Average assumed reinsurance amounts to the size of 16.3% of total premiums written. These reinsurance premiums include both, life and non-life reinsurance

[23]The difference to 100% is explained by rounding errors.

business, although insurers typically cede more non-life than life insurance to reinsurers.[24] 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.

3.4 Life Business

Hypothesis ($H1$) states that contagion risk exhibits a u-shaped relation with the fraction of life business. We examine the hypothesis in the following baseline OLS panel regression:

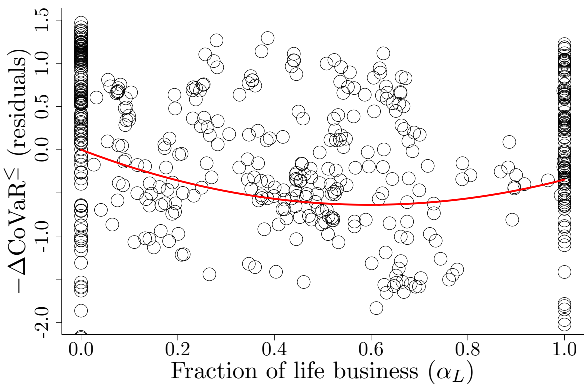
$$Y_{i,t} = \beta_0 + \beta_{life,1}\, Life^2_{i,t-1} + \beta_{life,2}\, Life_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}. \tag{10}$$

$Y_{i,t}$ is the respective contagion 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 contagion risk measures and insurer characteristics, we lag all explanatory variables based on accounting statements by one year.[25] We include time-fixed effects β_t and compute insurer-clustered standard errors. The squared term of the fraction of life business ratio is the main feature of our model in order to test for a u-shaped relation between contagion risk and life business. It is also the main difference to previous empirical studies about contagion risk and insurance companies' characteristics.

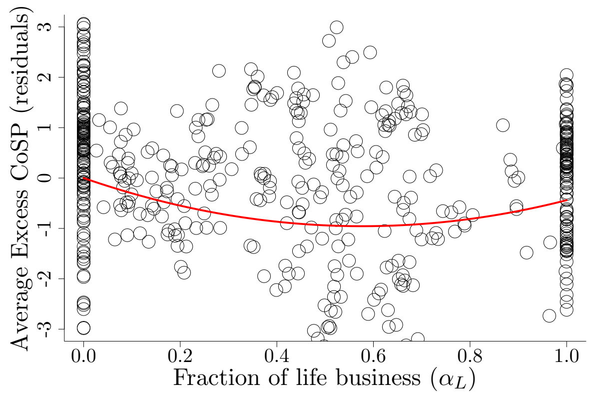
Figure 7 depicts the residuals of Regression (10) with respect to the American non-financial sector (AMC) when not including life premiums as explanatory variable. Clearly, there is a downward trend in contagion risk for small levels of life premiums (α_L) and an upward trend for larger levels. This evolution is particularly clear for $-\Delta\text{CoVaR}^{\leq}$ and implies a contagion-risk minimizing fraction of life business at approximately $\alpha_L^* = 59\%$. While it seems that the diversification effect is smaller with respect to the Average Excess CoSP, the regression results imply that it is significant, as well.

[24] 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.

[25] We find very similar results if we instead lag explanatory variables by one year. The results are available on request by the authors.



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



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

Figure 7: Residuals of Regression (10) when not including life premiums as explanatory variable (black points) and fitted effect of the fraction of life business (red, straight line). Contagion risk measures are computed with respect to the American non-financial sector (AMC) for insurers in our baseline sample.

The estimated coefficients are presented in Table 4. We find that the fraction of life business is significantly related to contagion 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 contagion risk measures we find that $\beta_{life,1} > 0$ and $\beta_{life,2} < 0$. This implies a u-shaped dependence between contagion risk and life business as illustrated in Figure 7. This finding confirms the intuition of our theoretical model from Section 2 and hypothesis ($H1$).

The effects of our control variables on the contagion risk measures is in line with the results of Weiß and Mühlnickel (2014), Berdin and Sottocornola (2015), Bierth et al. (2015), and the intuition presented above: Size as measured by log total assets as well as leverage have a positive effect on contagion risk, while the effect of the market-to-book ratio tends to be negatively related to contagion risk. The only significant control variables with respect to $\Delta\text{CoVaR}^{\leq}$ are size and leverage, which is in line with the findings of Weiß and Mühlnickel (2014) and Bierth et al. (2015).

Although we find the relation between contagion 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 case, we compute the implied contagion-risk minimizing fraction of life business. This is given as the minimum to the function $Y_{i,t}$ in Equation (10) with respect to Life. Since $Y_{i,t}$ is convex in Life,

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta$CoVaR$^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta$CoVaR$^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	0.555**	0.333**	0.663***	0.621**
	(0.249)	(0.162)	(0.247)	(0.245)
Life	$-$0.670**	$-$0.383**	$-$0.764***	$-$0.738***
	(0.273)	(0.185)	(0.270)	(0.272)
Log.Total.Assets	0.020	0.039***	0.027*	0.063***
	(0.017)	(0.009)	(0.016)	(0.016)
Market.to.Book	$-$0.031	$-$0.027	$-$0.042	$-$0.046
	(0.028)	(0.021)	(0.028)	(0.032)
RoE	$-$0.065	0.031	0.043	0.179
	(0.229)	(0.066)	(0.217)	(0.139)
Leverage	0.015***	0.006***	0.018***	0.017***
	(0.003)	(0.002)	(0.003)	(0.005)
Constant	0.292	$-$0.195	0.143	$-$0.659**
	(0.286)	(0.144)	(0.280)	(0.257)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	46.3	$-$620.2	17	$-$169.4
Observations	534	534	533	533
R^2	0.581	0.655	0.585	0.603
Adjusted R^2	0.570	0.645	0.574	0.592
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Baseline OLS Regression (10) 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. The contagion risk measures are standardized. Robust standard errors are clustered by insurers and reported in parentheses.

it results from the first-order condition which is

$$\alpha_L^* = -\frac{\beta_{life,2}}{2\beta_{life,1}}. \tag{11}$$

In Table 5 we report the resulting contagion-risk minimizing fractions of life business α_L^*. First, we observe that α_L^* is larger than 50% for all combinations of contagion risk measures and sectors. This confirms hypothesis $(H2)$ and is consistent with life business having a smaller volatility than non-life business. Second, the contagion-risk minimizing fraction of life business (α_L^*) is very similar across different measures and with respect to different sectors. Therefore, we find our result to be very robust.

The impact of life insurance is not only statistically significant in our baseline model, it is also economically significant: A fraction of life business that deviates by one standard deviation from

Contagion Risk Measure	FIN	AMC
Average Excess CoSP	0.60	0.58
$-\Delta\text{CoVaR}^{\leq}$	0.57	0.59

Table 5: contagion-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 contagion-risk minimizing fraction (α_L^*) is related to an increase of roughly 25% to 30% of long-term contagion risk (as measured by the Average Excess CoSP) and of roughly 8% to 17% of short-term contagion risk (as measured by $-\Delta\text{CoVaR}^{\leq}$) for the median insurer in our sample. The sensitivities are reported in Table 6. This result highlights the importance of life business for long-term contagion risk: As life business increases the long-term stability of cash flows, its diversification effect is larger on the Average Excess CoSP than on $-\Delta\text{CoVaR}^{\leq}$. For example, an increase in the fraction of life business from 0.6 to 0.98 is, on average, related to an increase in the Average Excess CoSP (i.e. the average excess probability of a sector's distress after an insurer's distress) of the FIN sector from 0.32 to 0.4.

Contagion Risk Measure	FIN	AMC
Average Excess CoSP	25%	30%
$-\Delta\text{CoVaR}^{\leq}$	8%	17%

Table 6: Relative change in contagion 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 relative to the contagion-risk minimizing fraction of life business (α_L^*) for the median insurer in our baseline sample.

In contrast to our baseline model, the relation between contagion risk measures and explanatory variables might be nonlinear, in general. Since $\Delta\text{CoVaR}^{\leq}$ reflects the quantile of log returns, we examine additional panel regressions with $\exp(\Delta\text{CoVaR}^{\leq})$ that 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 14 in Appendix B.3. Our baseline results remain the same. Furthermore, in an unreported regression we also apply 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 in all model set-ups.[26]

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 insurance business reduces the risk remaining on an insurer's balance sheet and, thus, might have an impact on contagion 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 15 in Appendix B.3. As in our baseline results, the contagion risk measures are highly significantly related to the fraction of life business in a u-shaped functional form.

An 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 cannot only be caused by a large number of life insurance policies sold but also by a long duration of life policies. Since we have argued that 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 life premiums by life reserves for U.S. insurance holdings as reported by A.M. Best Company. Indeed, we do not find a significant diversification effect between life and non-life business and only a very weak effect of life business on contagion risk measures.

In our baseline regressions we do not include insurer-fixed effects. Since most explanatory variables are very persistent over time for each insurer, including insurer-fixed effects would dramatically reduce the available dispersion in the explanatory variables to explain the contagion risk measures, particularly due to the small time period of our sample.[27] This would substantially increase the parameter uncertainty in our model and, thus, reduce the statistical significance of the coefficients. Without insurer-fixed effects we are able to base our estimation on differences across insurers as well as within insurers, which makes our estimates more robust. Indeed, including insurer-fixed effects raises R^2 up to 93% and renders almost all explanatory variables insignificant at the 10% level.[28] This suggests substantial overfitting of the model.

[26] Both additional set-ups also confirm the robustness of other OLS regressions employed in this article. The results are available on request by the authors.

[27] Note that we control for the persistence of explanatory variables by computing standard errors clustered by insurers.

[28] The only exception is that leverage is still significant at the 5% level.

Therefore, our results 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 16 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). We find significant diversification benefits particularly for $\Delta\text{CoVaR}^{\leq}$ and the contagion-risk minimizing fraction of life business is similar to our baseline result. Since, in these cross-sectional regressions, the first year that is used for the estimation of the contagion risk measures is 2009, this analysis also suggests that the financial crisis 2007-2008 is not a driver for our baseline results.

Financial contagion might depend on the location of insurers. For example, U.S. insurers might exhibit a larger degree of financial contagion 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 17 in Appendix B.3. Indeed, we find significant differences in the contagion risk between African, Australian, Japanese and European insurers, respectively. Differences between European and North American insurers remain insignificant. Moreover, in all regressions except for $\Delta\text{CoVaR}^{\leq}$ with respect to the American non-financial sector we still find the quadratic term of life business significantly positive and the linear term significantly negative at the 1% level, i.e. significant diversification. The implied contagion-risk minimizing fractions of life business remain close to our baseline results.

One concern about the use of contagion 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 present particularly for $\Delta\text{CoVaR}^{\leq}$ as its correlation with systematic risk is larger than that for the Aggregate Excess CoSP. Therefore, if indeed our returns were driven by instantaneous correlation of financial market returns, this effect would be particularly large with respect to $\Delta\text{CoVaR}^{\leq}$. However, Table 6 shows that the effect 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.

3.5 Non-Core Insurance Activities

Life insurers typically conduct more non-core insurance business than non-life insurers.[29] 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. Similarly to Bierth et al. (2015), we approximate non-core insurance activities by the ratio of total liabilities over insurance reserves. Indeed, non-core activities tend to exhibit a positive relation with long-term contagion risk (see Table 18 in Appendix B.3). However, these activities neither alter the significance of the quadratic interaction between contagion risk and the fraction of life business nor impact the implied contagion-risk minimizing fraction of contagion risk, as reported in Table 7. We conclude that non-core insurance activities do not explain our results.

Contagion Risk Measure	FIN	AMC
Average Excess CoSP	0.59	0.56
$-\Delta\text{CoVaR}^{\leq}$	0.57	0.58

Table 7: Contagion-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 controlling for non-core insurance activities.

3.6 Investment Volatility

In our model, the effect of investment volatility on diversification depends on differences in the expected return from insurance activities. The empirical analysis of insurance underwriting growth of U.S. insurers in Section 2.1 suggests that the expected return from life insurance activities is larger than that from non-life insurance activities. Based on this observation, in hypothesis ($H3$) we expect that the contagion-risk minimizing fraction of life business increases with investment volatility. As a measure for the volatility of an insurance holding's investments, we employ the total fraction of equity stock investments in a particular year. We interact life business with stocks

[29] 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.

in the following regression model:

$$
\begin{aligned}
Y_{i,t} =& \beta_0 + \beta_{life,1}\, Life^2_{i,t-1} + \beta_{life,2}\, Life_{i,t-1} + \beta_{life,stocks}\, Life_{i,t-1} * Stocks_{i,t-1} \\
& + \beta_{stocks}\, stocks_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}.
\end{aligned} \tag{12}
$$

The results can be found in Appendix B.3 in Table 19. The contagion-risk minimizing fraction of life business in this model is given as

$$
\alpha_L^* = -\frac{\beta_{life,2} + \beta_{life,stocks} Stocks}{2\beta_{life,1}}. \tag{13}
$$

In general, we find that the interaction term, $\beta_{life,stocks}$, tends to be negative but not significantly different from zero at the 10% level (see Table 19). Thus, as $\beta_{life,1} > 0$, the contagion-risk minimizing fraction tends to increase with stock investments, which is consistent with hypothesis ($H3$). In our model, this result arises if the expected return from insurance activities is larger for life than non-life insurance. Differences in returns can arise, for example, if competition is smaller in life insurance and, thus, premium loadings are larger. Indeed, Cummins et al. (1999) notes that competition in the life insurance industry is traditionally very low. One reason might be the heterogeneity of life insurance, particularly savings, products across insurers.

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.

3.7 Leverage

The theoretical model suggests that the contagion-risk minimizing fraction of life insurance is decreasing with leverage (hypothesis (($H4$)). We examine whether this hypothesis is empirically supported by interacting leverage and life business in the following regression:

$$\begin{aligned} Y_{i,t} =&\beta_0 + \beta_{life,1}\, life^2_{i,t-1} + \beta_{life,2}\, Life_{i,t-1} + \beta_{life,lev}\, Life_{i,t-1} * Leverage_{i,t-1} \\ &+ \beta_{lev}\, Leverage_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}. \end{aligned} \tag{14}$$

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

$$\alpha^*_L = -\frac{\beta_{life,2} + \beta_{life,lev,2} Leverage}{2\beta_{life,1}}. \tag{15}$$

Since $\beta_{life,1} > 0$ and $\beta_{life,lev} < 0$ in Table 20, our results imply that α^*_L is increasing with an insurer's leverage for all contagion risk measures. This is consistent with hypothesis ($H4$). As in hypothesis ($H3$), in our model, this result arises if the expected return from insurance activities is larger for life than for non-life business. However, as $\beta_{life,lev}$ is significantly different from zero at the 5% level only for $-\Delta$CoVaR$^{\leq}$ (AMC), we find that it does not have an important effect on diversification.

In addition to the previous model that assumes a linear effect of leverage on α^*_L, we also control for a non-linear effect of leverage by interacting it with Life^2 as well. The results remain unchanged.

3.8 Reinsurance Business

Since primary insurance and reinsurance liabilities are strongly correlated, in hypothesis ($H5$) we only expect a small or even no diversification effect between primary insurance and active reinsurance business with respect to contagion risk. Indeed, in Table 21 in Appendix B.3 we do not find a significant quadratic interaction between reinsurance business assumed and contagion risk.[30]

However, given that reinsurance, non-life, and life business have different return characteristics, there might be a diversification effect between the three. Due to the high tail risk of reinsurance, we expect the contagion-risk minimizing fraction of life business to increase with reinsurance business (hypothesis ($H6$)). We interact life business with reinsurance business in the following regression

[30] Table 21 in Appendix B.3 reports the results of the OLS regression

$$Y_{i,t} = \beta_0 + \beta_{reins,1} Reinsurance^2_{i,t} + \beta_{reins,2} Reinsurance_{i,t} + \beta_Z Z_{i,t-\tau} + \beta_t + \varepsilon_{i,t}. \tag{16}$$

We do not find $\beta_{reins,1}$ to be significantly different from zero at the 5% level. Moreover, $\beta_{reins,1}$ tends to be negative.

model

$$Y_{i,t} = \beta_0 + \beta_{life,1}\, Life^2_{i,t-1} + \beta_{life,2}\, Life_{i,t-1} + \beta_{life,reins,2}\, Life_{i,t-1} * Reinsurance_{i,t-1} \\ + \beta_{reins}\, Reinsurance_{i,t-1} + \beta_Z Z_{i,t-1} + \beta_t + \varepsilon_{i,t}. \tag{17}$$

The estimated coefficients can be found in Table 22 in Appendix B.3. Although we do not find the interaction between reinsurance and life business to be statistically significant, reinsurance tends to intensify the diversification benefits of life insurance business since $\beta_{life,reins,2} < 0$ for most considered risk-measure-sector pairs. Thus, the contagion-risk minimizing fraction of life business tends to increase with reinsurance business.

In addition to the previous model that assumes a linear effect of leverage on α^*_L, we also control for a non-linear effect of reinsurance assumed by interacting it with Life^2 as well. We find that active reinsurance tends to increase the contagion-risk minimizing fraction of life business only for long-term contagion risk with respect to the financial sector and short-term financial contagion with respect to the American non-financial sector. However, the interaction between active reinsurance and life business remains insignificant. We conclude that active reinsurance only exhibits a weak impact on contagion-risk diversification between life and non-life insurance.

4 Costs and Benefits of Diversification and Policy Implications

Our previous results imply that diversification of life and non-life insurance activities decreases the risk of financial contagion amplified by multiline insurance companies in comparison to mono-liners. The average size of life business in our sample is slightly smaller than the level we have found to minimize spillover risk on average.[31] This result raises two important questions, namely whether macro-prudential regulation should incentivize raising life insurance activities to increase diversification across insurance lines, and what costs and benefits for the companies themselves are associated with the allocation of insurance business.

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

[31] The mean fraction of life business in our sample is 44.2% and the median level 44%. In the baseline regressions in Section 3.4 we find a fraction of roughly 58% of life business to minimize financial contagion on average.

(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 reason is that, if both banks fully diversify, they hold identical portfolios and will either not fail together or fail together. The central assumption in both articles is, that higher homogenization increases the correlation of exposures.

This argument is not necessarily fully applicable to the insurance sector: First, the majority of claims of different policyholders are typically uncorrelated, as e.g. claims from car accidents or private liability insurance.[32] 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. Hence, although geographic diversification can be desirable for insurance companies, particularly for reinsurance companies, it is not necessary to achieve diversification benefits between life and non-life insurance.

Therefore, the effect of a higher overall level of diversification among 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 as these engage in the same insurance activities. This applies to catastrophic events, in particular, that affect many policyholders simultaneously. Then, a high degree of correlation among exposures might raise the likelihood of joint failures and systemic crises within the insurance sector. On the other hand, due to small correlations among claims related to non-catastrophic events, diversification of insurance activities might reduce the risk of financial contagion from insurance companies to other financial institutions. This trade off suggests, that macro-prudential regulation should neither unambiguously reward diversification of business activities nor fully disregard it. Instead, it should account for the stabilizing effect of diversification with respect to financial contagion while recognizing the joint exposure to risks that might arise from diversification.

While diversification reduces the business volatility, it might also evoke costs to insurers and policyholders. For example, consider one monoline and one multiline insurance companies that have the same size. Then, the monoline insurance company will typically have a higher degree

[32] 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.

diversification within insurance pools, as it sells more similar contracts 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 multiliner (Albrecht (1990)). 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 the sense of Panzar and Willig (1981), as the costs of providing both life and non-life insurance are subadditive in terms of volatility. As our analysis shows, such economies of scope can lower the risk of financial contagion and credit risk in particular, which might also result in lower financing costs. Eventually, the difference between multiline and monoline insurers is characterized by the 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.[33] 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), 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 efficient than monoline insurers.

In conclusion, we find that diversification between life and non-life insurance activities increases benefits from economies of scope but reduces benefits from economies of scale. While the first effect dominates with respect to financial contagion by reducing the probability of shock transmission, the second effect dominates with respect to profitability by decreasing the possibility to pool risks.

[33] The estimated coefficients can be found in Table 23 in Appendix B.3.

5 Conclusion

In this article, we examine the impact of insurance business activities on contagion risk, i.e. the propensity of insurance companies to transmit economic shocks to other institutions. We identify two stylized differences between non-life and life insurance business, namely that cash flows in life insurance are less volatile and not perfectly correlated to non-life insurance cash flows. 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 contagion risk in general.

Our model makes several predictions about the contagion-risk minimizing fraction of life business, namely that it is larger than 50%, and increasing with the volatility of investments and an insurer's leverage. We confirm these predictions in an empirical analysis of international insurance companies by means of spillover 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 contagion risk.

The results in this article contribute to the discussion on how to decrease financial contagion among financial institutions. With respect to insurance holdings, our findings suggest that macro-prudential regulation should reward a diversified insurance product portfolio in terms of life and non-life insurance contracts that balances long-term exposure to economic shocks as well as volatility. Since the contagion-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)). The same rationale applies to the risk management of other institutions that engage in financial transactions with insurance companies, e.g. by holding subordinated debt.

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*

$$\alpha_L^* = \frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho}. \tag{18}$$

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 volatility of the life (non-life) business, if ρ is sufficiently small.

Proof. The marginal expected loss is equal to

$$\frac{dEL}{d\alpha_L} = -\frac{d\mu}{d\alpha_L}\Phi\left(\frac{D-\mu}{\sigma}\right) + \frac{d\sigma}{d\alpha_L}\varphi\left(\frac{D-\mu}{\sigma}\right). \tag{19}$$

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

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

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

$$\frac{d\sigma^2}{d\alpha_L} = 0 \tag{21}$$

$$2\alpha_L\sigma_L^2 - 2(1-\alpha_L)\sigma_{NL}^2 + 2(1-2\alpha_L)\sigma_L\sigma_{NL}\rho = 0 \tag{22}$$

$$\alpha_L\left(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho\right) - \sigma_{NL}^2 + \sigma_L\sigma_{NL}\rho = 0 \tag{23}$$

$$\alpha_L^* = \frac{\sigma_{NL}^2 - \sigma_L\sigma_{NL}\rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho} \tag{24}$$

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

$$\frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho} < 1 \tag{25}$$

$$\Leftrightarrow \quad \sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho < \sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho \tag{26}$$

$$\Leftrightarrow \quad 0 < \sigma_L \left(\sigma_L - \sigma_{NL} \rho\right) \tag{27}$$

$$\Leftrightarrow \quad \rho < \frac{\sigma_L}{\sigma_{NL}} \tag{28}$$

and

$$\frac{\sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L \sigma_{NL} \rho} > 0 \tag{29}$$

$$\Leftrightarrow \quad \sigma_{NL}^2 - \sigma_L \sigma_{NL} \rho > 0 \tag{30}$$

$$\Leftrightarrow \quad \frac{\sigma_{NL}}{\sigma_L} > \rho \tag{31}$$

A marginal change in the life return volatility yields

$$\frac{d\alpha_L^*}{d\sigma_L} = \frac{-\sigma_{NL}\rho(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho) - (\sigma_{NL}^2 - \sigma_L\sigma_{NL}\rho)(2\sigma_L - 2\sigma_{NL}\rho)}{(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho)^2} \tag{32}$$

$$= \frac{\sigma_{NL}\rho\sigma_L^2 - \sigma_{NL}\rho\sigma_{NL}^2 - \sigma_{NL}^2(2\sigma_L - 2\sigma_{NL}\rho)}{(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho)^2} \tag{33}$$

$$= \sigma_{NL} \frac{\rho(\sigma_L^2 + \sigma_{NL}^2) - 2\sigma_{NL}\sigma_L}{(\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho)^2}, \tag{34}$$

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. □

Lemma 2. *Assume that the expected returns from life and non-life business do not differ and that their correlation is nonnegative. If the return from life business is less volatile than that from non-life business, the credit-risk minimizing fraction of life business is larger than 50%.*

Proof. 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

$$\frac{\sigma_{NL}^2 - \sigma_L\sigma_{NL}\rho}{\sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho} > 1/2 \tag{35}$$

$$\Leftrightarrow \quad 2\sigma_{NL}^2 - \sigma_L\sigma_{NL}\rho > \sigma_L^2 + \sigma_{NL}^2 - 2\sigma_L\sigma_{NL}\rho \tag{36}$$

$$\Leftrightarrow \quad \frac{\sigma_{NL}^2 - \sigma_L^2}{\sigma_L\sigma_{NL}} > -\rho, \tag{37}$$

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

Lemma 3. *Assume that the return from life business is less volatile and larger in expectation than that from non-life business. If, equity capital is sufficiently small,* $\alpha_L^* = 1$.

Proof. The return volatility is given by

$$\sigma^2 = \alpha_L^2\sigma_L^2 + (1-\alpha_L)^2\sigma_{NL}^2 + 2\alpha_L(1-\alpha_L)\sigma_L\sigma_{NL}\rho \tag{38}$$

and the expected return by

$$\mu = OF + \alpha_L\mu_L + (1-\alpha_L)\mu_{NL}. \tag{39}$$

For decreasing OF it is

$$\lim_{OF\to-\infty}\frac{D-\mu}{\sigma} = \lim_{OF\to-\infty}\frac{D - OF - (\alpha_L\mu_L + (1-\alpha_L)\mu_{NL})}{\sqrt{\alpha_L^2\sigma_L^2 + (1-\alpha_L)^2\sigma_{NL}^2 + 2\alpha_L(1-\alpha_L)\sigma_L\sigma_{NL}\rho}} \tag{40}$$

$$= \infty \tag{41}$$

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

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

$$INDEX_t^{\mathbb{S}|j} = INDEX_{t-1}^{\mathbb{S}|j} \sum_{s \in \mathbb{S} \setminus \{j\}} \frac{MC_{s,t-1}}{\sum_{i \in \mathbb{S} \setminus \{j\}} MC_{i,t-1}} \frac{TR_{s,t}}{TR_{s,t-1}}. \tag{42}$$

To compute the return based contagion 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).[34] 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.

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

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.

Top 10 Companies	Industrial Sectors
APPLE	Technology Hardware and Equipment
EXXON MOBIL	Oil and Gas Producers
MICROSOFT	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 OF 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	WHITE MOUNTAINS IN.GP.
36	MANULIFE FINANCIAL	WUESTENROT & WUERTT.
37	MAPFRE	ZURICH INSURANCE GROUP
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 OF 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	WHITE MOUNTAINS IN.GP.
21	LINCOLN NATIONAL	WUESTENROT & WUERTT.
22	MAPFRE	ZURICH INSURANCE GROUP

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 ΔCoVaR$^{\leq}$	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.	ORBIS
reinsurance to total gross premiums written.	Ratio of premiums assumed in active reinsurance	ORBIS
Total assets	An insurer's total assets.	ORBIS / Worldscope (WC02999)
Leverage	Ratio of total equity to assets (in book values).	Worldscope (WC02999, WC03501)
Market-to-Book	Ratio of market value equity to book value equity.	Worldscope (WC07210, WC03501)
RoE	Return on equity per share. with a maturity of at least 1 year at the time of purchase.	Worldscope (WC08372)

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*.

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	0.671***	0.013***	0.804***	0.025***
	(0.121)	(0.002)	(0.119)	(0.004)
Life	−0.782***	−0.015***	−0.903***	−0.029***
	(0.125)	(0.002)	(0.124)	(0.004)
Log.Total.Assets	0.016*	0.001***	0.025***	0.002***
	(0.009)	(0.0002)	(0.009)	(0.0003)
Market.to.Book	−0.032*	−0.001***	−0.046**	−0.002***
	(0.020)	(0.0004)	(0.020)	(0.001)
RoE	−0.142	0.001	−0.056	0.007*
	(0.095)	(0.002)	(0.097)	(0.004)
Leverage	0.010***	0.0002***	0.012***	0.001***
	(0.002)	(0.0001)	(0.002)	(0.0001)
Constant	−0.745***	0.955***	−0.929***	0.936***
	(0.181)	(0.003)	(0.180)	(0.005)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	46.3	−4112	25.7	−3619.1
Observations	534	534	533	533
Akaike Inf. Crit.	46.278	-4,111.957	25.710	-3,619.143
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 14: Robustness OLS Regression (10) 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). All contagion risk measures are standardized.

	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)	0.543^{**}	0.289^{*}	0.671^{***}	0.568^{**}
	(0.256)	(0.164)	(0.255)	(0.248)
Life (net)	-0.658^{**}	-0.353^{*}	-0.775^{***}	-0.720^{***}
	(0.279)	(0.188)	(0.278)	(0.276)
Log.Total.Assets	0.026	0.045^{***}	0.033^{**}	0.073^{***}
	(0.017)	(0.009)	(0.016)	(0.015)
Market.to.Book	-0.027	-0.024	-0.037	-0.034
	(0.028)	(0.021)	(0.028)	(0.031)
RoE	-0.063	0.027	0.040	0.147
	(0.242)	(0.065)	(0.228)	(0.129)
Leverage	0.013^{***}	0.005^{**}	0.016^{***}	0.016^{***}
	(0.003)	(0.002)	(0.003)	(0.005)
Constant	0.185	-0.300^{**}	0.029	-0.851^{***}
	(0.284)	(0.135)	(0.272)	(0.246)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	31.6	-600.7	-4.9	-185.1
Observations	501	501	500	500
R^2	0.584	0.672	0.593	0.625
Adjusted R^2	0.572	0.663	0.581	0.614
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15: Robustness OLS Regression (10) 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). All contagion risk measures are standardized.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta$CoVaR$^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta$CoVaR$^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	0.449	0.871***	0.652	0.494**
	(0.445)	(0.325)	(0.442)	(0.207)
Life	-0.679	-0.987^{***}	-0.919^{**}	-0.567^{**}
	(0.457)	(0.342)	(0.459)	(0.221)
Log.Total.Assets	0.111***	0.082***	0.108***	0.037**
	(0.027)	(0.021)	(0.028)	(0.015)
Market.to.Book	-0.100	-0.024	-0.118^{*}	-0.020
	(0.068)	(0.056)	(0.070)	(0.034)
RoE	0.444	-0.225	0.735	-0.193
	(0.791)	(0.526)	(0.809)	(0.347)
Leverage	0.033***	0.016***	0.039***	0.013***
	(0.011)	(0.006)	(0.011)	(0.004)
Constant	-0.886^{*}	-0.330	-0.830^{*}	0.437*
	(0.466)	(0.340)	(0.468)	(0.245)
Akaike Inf. Crit	56.4	12.3	58	-41.3
Observations	72	72	71	71
R^2	0.354	0.331	0.382	0.273
Adjusted R^2	0.294	0.269	0.324	0.204
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16: 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 ΔCoVaR$^{\leq}$ 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	0.653**	0.301**	0.666**	0.352
	(0.272)	(0.125)	(0.274)	(0.244)
Life	−0.757**	−0.307**	−0.750**	−0.440
	(0.301)	(0.148)	(0.306)	(0.278)
Continent:AFRICA	−0.251***	−0.275***	−0.278***	−0.260***
	(0.063)	(0.045)	(0.058)	(0.082)
Continent:ASIA	−0.048	−0.124**	−0.043	−0.116*
	(0.075)	(0.058)	(0.081)	(0.062)
Continent:AUSTRALIA	−0.232***	−0.137***	−0.218***	−0.388***
	(0.049)	(0.026)	(0.050)	(0.056)
Continent:JAPAN	−0.143**	−0.089***	−0.166***	−0.272***
	(0.062)	(0.024)	(0.062)	(0.063)
Continent:NORTH AMERICA	−0.045	−0.023	0.00004	0.122*
	(0.065)	(0.041)	(0.065)	(0.072)
Log.Total.Assets	0.018	0.028***	0.024	0.054***
	(0.019)	(0.009)	(0.019)	(0.014)
Market.to.Book	−0.001	0.004	−0.009	−0.001
	(0.025)	(0.015)	(0.025)	(0.022)
RoE	−0.062	0.032	0.039	0.127
	(0.230)	(0.055)	(0.214)	(0.110)
Leverage	0.015***	0.005	0.016***	0.009*
	(0.004)	(0.003)	(0.004)	(0.005)
Constant	0.308	−0.045	0.150	−0.643***
	(0.324)	(0.141)	(0.315)	(0.226)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	29.9	−715.7	−8.1	−304.6
Observations	534	534	533	533
R^2	0.601	0.717	0.612	0.697
Adjusted R^2	0.587	0.706	0.597	0.686
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 17: 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)	$-\Delta$CoVaR$^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta$CoVaR$^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	0.583**	0.337**	0.696***	0.662***
	(0.256)	(0.164)	(0.253)	(0.244)
Life	$-$0.688**	$-$0.386**	$-$0.785***	$-$0.765***
	(0.277)	(0.187)	(0.274)	(0.273)
Non-core Activities	0.0005***	$-$0.0001	0.0003*	$-$0.001***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Log.Total.Assets	0.020	0.039***	0.026	0.063***
	(0.017)	(0.009)	(0.016)	(0.015)
Market.to.Book	$-$0.032	$-$0.027	$-$0.044	$-$0.050
	(0.028)	(0.021)	(0.028)	(0.033)
RoE	$-$0.115	0.026	$-$0.011	0.137
	(0.216)	(0.066)	(0.202)	(0.127)
Leverage	0.014***	0.006***	0.017***	0.017***
	(0.003)	(0.002)	(0.003)	(0.005)
Constant	0.309	$-$0.194	0.162	$-$0.642**
	(0.285)	(0.144)	(0.278)	(0.254)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	38.5	$-$611.6	8.6	$-$173.5
Observations	531	531	530	530
R^2	0.587	0.655	0.591	0.609
Adjusted R^2	0.575	0.645	0.579	0.597
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: 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 ΔCoVaR$^{\leq}$ 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)	$-\Delta$CoVaR$^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta$CoVaR$^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Life^2	0.487**	0.303**	0.606**	0.627***
	(0.241)	(0.143)	(0.236)	(0.243)
Life	$-$0.586**	$-$0.338**	$-$0.673***	$-$0.677***
	(0.252)	(0.152)	(0.248)	(0.263)
Stocks	$-$0.409	$-$0.410	$-$0.418	$-$0.131
	(0.409)	(0.288)	(0.399)	(0.468)
Log.Total.Assets	0.018	0.038***	0.024	0.061***
	(0.016)	(0.008)	(0.015)	(0.014)
Market.to.Book	0.0003	$-$0.002	$-$0.009	$-$0.030
	(0.032)	(0.024)	(0.032)	(0.037)
RoE	$-$0.103	0.030	$-$0.003	0.119
	(0.207)	(0.051)	(0.194)	(0.123)
Leverage	0.013***	0.003*	0.015***	0.014***
	(0.003)	(0.002)	(0.003)	(0.005)
Life:Stocks	$-$0.475	$-$0.421	$-$0.667	$-$0.829
	(0.580)	(0.437)	(0.573)	(0.668)
Constant	0.328	$-$0.177	0.182	$-$0.638***
	(0.279)	(0.124)	(0.264)	(0.242)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	15.1	$-$655.9	$-$19.4	$-$187
Observations	519	519	518	518
R^2	0.603	0.694	0.613	0.623
Adjusted R^2	0.590	0.684	0.600	0.611
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 19: OLS Regression (13) 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 ΔCoVaR$^{\leq}$ with respect to the global financial sector (FIN) and the American non-financial sector, respectively. The contagion risk measures are standardized. 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	0.500^{*}	0.315^{*}	0.623^{**}	0.638^{**}
	(0.257)	(0.169)	(0.255)	(0.251)
Life	-0.581^{**}	-0.334	-0.675^{**}	-0.645^{**}
	(0.291)	(0.204)	(0.288)	(0.297)
Leverage	0.022^{***}	0.012^{**}	0.027^{***}	0.035^{***}
	(0.008)	(0.005)	(0.008)	(0.010)
Log.Total.Assets	0.018	0.038^{***}	0.025	0.060^{***}
	(0.017)	(0.010)	(0.017)	(0.016)
Market.to.Book	-0.027	-0.028	-0.041	-0.059^{*}
	(0.028)	(0.021)	(0.028)	(0.034)
RoE	-0.062	0.063	0.055	0.277^{**}
	(0.221)	(0.059)	(0.202)	(0.114)
Life:Leverage	-0.009	-0.008	-0.012	-0.025^{**}
	(0.009)	(0.006)	(0.009)	(0.010)
Constant	0.298	-0.206	0.148	-0.665^{***}
	(0.294)	(0.147)	(0.288)	(0.247)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	32.6	-593.9	5.7	-187.5
Observations	519	519	518	518
R^2	0.588	0.654	0.592	0.622
Adjusted R^2	0.576	0.644	0.580	0.611
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 20: OLS Regression (15) with Leverage.

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. The contagion risk measures are standardized. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$ (FIN)	$-\Delta$CoVaR$^{\leq}$ (FIN)	$\bar{\psi}$ (AMC)	$-\Delta$CoVaR$^{\leq}$ (AMC)
	(1)	(2)	(3)	(4)
Reinsurance^2	-0.302	-0.057	-0.328	-0.606^{*}
	(0.408)	(0.205)	(0.413)	(0.339)
Reinsurance	0.348	0.080	0.381	0.656^{**}
	(0.412)	(0.196)	(0.406)	(0.310)
Log.Total.Assets	0.001	0.021^{***}	0.004	0.030^{*}
	(0.023)	(0.007)	(0.021)	(0.016)
Market.to.Book	0.003	-0.010	-0.023	-0.064
	(0.044)	(0.020)	(0.044)	(0.047)
RoE	-0.121	0.016	-0.017	0.028
	(0.280)	(0.064)	(0.266)	(0.135)
Leverage	0.017^{***}	0.005^{***}	0.022^{***}	0.017^{***}
	(0.004)	(0.002)	(0.004)	(0.004)
Constant	0.437	0.054	0.354	-0.164
	(0.397)	(0.123)	(0.369)	(0.288)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	27.3	-622.6	-7.1	-208.8
Observations	328	328	328	328
R^2	0.509	0.638	0.517	0.592
Adjusted R^2	0.487	0.621	0.495	0.573
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: OLS Regression (16) 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 ΔCoVaR$^{\leq}$ with respect to the global financial sector (FIN) and the American non-financial sector (AMC), respectively. The contagion risk measures are standardized. 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	0.627*	0.148	0.738**	0.421
	(0.363)	(0.207)	(0.354)	(0.310)
Life	−0.708*	−0.150	−0.843**	−0.525
	(0.399)	(0.238)	(0.391)	(0.346)
Reinsurance	0.121	0.037	0.081	0.188
	(0.135)	(0.053)	(0.141)	(0.130)
Log.Total.Assets	0.032	0.026**	0.041*	0.056***
	(0.024)	(0.011)	(0.022)	(0.018)
Market.to.Book	−0.019	−0.013	−0.049	−0.083*
	(0.041)	(0.019)	(0.041)	(0.044)
RoE	−0.153	0.007	−0.055	0.015
	(0.257)	(0.059)	(0.236)	(0.115)
Leverage	0.013***	0.004*	0.016***	0.015***
	(0.004)	(0.002)	(0.004)	(0.005)
Life:Reinsurance	−0.053	−0.014	0.044	−0.131
	(0.147)	(0.062)	(0.141)	(0.144)
Constant	0.005	−0.019	−0.162	−0.527*
	(0.397)	(0.176)	(0.364)	(0.295)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	67.9	−428.6	39.2	−136.6
Observations	328	328	328	328
R^2	0.536	0.642	0.555	0.609
Adjusted R^2	0.512	0.623	0.532	0.589
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 22: Baseline OLS Regression (18) 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. The contagion risk measures are standardized. Robust standard errors are clustered by insurers and provided in parentheses.

	Dependent variable:			
	RoA		RoE	
	(1)	(2)	(3)	(4)
Life^2	1.913***	1.778***	0.449	−0.078
	(0.446)	(0.580)	(0.516)	(0.492)
Life	−2.054***	−2.058***	−0.259	0.188
	(0.454)	(0.614)	(0.501)	(0.518)
Log.Total.Assets	−0.102	−0.061	−0.011	0.027
	(0.064)	(0.054)	(0.049)	(0.048)
Leverage	−0.032*	−0.022	−0.034	−0.029
	(0.018)	(0.016)	(0.027)	(0.030)
Market.to.Book		0.311***		0.405***
		(0.083)		(0.060)
Non-core Activities		0.123		0.015
		(0.114)		(0.072)
Constant	3.050***	2.129*	1.369	0.047
	(1.113)	(1.179)	(0.855)	(0.821)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Continent Fixed Effects		*Y*		*Y*
Akaike Inf. Crit	1056.2	1056.2	1056.2	1056.2
Observations	526	526	526	526
R^2	0.193	0.316	0.132	0.261
Adjusted R^2	0.174	0.290	0.112	0.233
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 23: OLS Regression of Insurance Holdings' Profitability.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the standardized return on assets (RoA) and standardized 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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