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Persistence of Insurance Activities and Financial Stability*

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Abstract

Different insurance activities exhibit different levels of persistence of shocks and volatility. For example, life insurance is typically more persistent but less volatile than non-life insurance. We examine how diversification among life, non-life insurance, and active reinsurance business affects an insurer's contribution and exposure to the risk of other companies. Our model shows that a counterparty's credit risk exposure to an insurance group substantially depends on the relative proportion of the insurance group's life and non-life business. The empirical analysis confirms this finding with respect to several measures for spillover risk. The optimal proportion of life business that minimizes spillover risk decreases with leverage of the insurance group, and increases with active reinsurance business.

Keywords: Insurance Companies, Financial Stability, Persistence

JEL Classification: G01, G22, G23, G28

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1 Introduction

During the 2007-08 financial crisis, AIG became the first prominent example of an insurance company to require and receive a government bailout. Its central role and interconnectedness as a counterparty for other financial institutions made apparent the importance of insurance companies for overall financial stability (Billio et al. (2012)). As large-scale financial investors, European insurance companies, for instance, have a volume more than 60% of Europe's GDP in assets under management (European Systemic Risk Board (2015)), which impressively highlights their potential influence on and exposure to market movements. Additionally, as financial intermediaries, insurance companies provide essential services to the society and economy by assuming, pricing, transferring and diversifying risks (Thimann (2014)). Comparing the insurance sector to the banking sector, the general size of its core business activities is substantial. While the written premiums of European insurance companies amount to €1.2 trillion in 2015 with €1 trillion claim payments, the European banking sector's lending activity accumulates to €23.5 trillion and €16.8 trillion as deposits (Insurance Europe (2016) and European Banking Federation (2016)).[1] This large scale of the insurance sector inevitably rises the potential of insurance companies being too-big-to-fail and too-interconnected-to-fail, which both have proven their tremendous threat during the last global financial crisis.

In this article, we study to what extent diversification of an insurance group's traditional business activities, in terms of life, non-life and reinsurance business, affects the propagation of economic shocks by insurance companies.[2] Insurance groups typically do not undertake exclusively life, non-life, or direct reinsurance business, but often comprise several operating companies that conduct life, non-life and reinsurance business. For example, AXA, the largest insurer in our sample according to combined gross premiums written, collects roughly 65% of combined gross premiums in life insurance and 3% in assumed reinsurance. Similarly, the Munich Re Group, that includes Munich

[1]For US insurers and banks the relation in size is similar, see Board of the Governors of the federal reserve system (2016).

[2]Note that we usually refer to insurance companies as holdings of different sub-companies (i.e. operating companies). In this context, an insurance company (group) is able to pursue both life and non-life business, while this is usually prohibited by law for direct insurers.

Re, which is the largest reinsurer according to gross premiums in our sample, writes 53% in life and only 53% in assumed reinsurance gross premiums.[3] Due to the possibility to redistribute capital within an insurance group, it is the financial condition of the consolidated insurance group that ultimately determines the propagation of shocks, for example via counterparty credit risk. Due to substantial differences in the risk of different insurance lines, the mix of business activities can have a subtle impact on the propagation of shocks.

Previous studies do not allow for a potential risk diversification effect between different insurance business activities but focus on the relation of single business activities with economic shocks (for example Berdin and Sottocornola (2015), Weiß and Mühlnickel (2014) and Kaserer and Klein (2016)). With this approach the immediate issue arises, how to classify insurance companies. For example, Weiß and Mühlnickel (2014) split their sample in life and non-life companies. AXA would be classified as direct life insurer, since life insurance is the largest business line. In a similar reasoning, Munich Re would be classified as reinsurer. However, such an approach does not adequately reflect the insurance group's risks, as life insurance and reinsurance are only part of the insurance activities of AXA and Munich Re, respectively. Due to fundamental differences in insurance lines, it seems intuitive that conducting both life and non-life business can reduce risks in comparison to exclusive life or non-life business. This intuition is also supported from a micro-prudential perspective of the European regulatory regime Solvency II, which explicitly allows for risk mitigation between life and non-life insurance business (European Commission (2015)). Confirming this rationale, Berdin et al. (2016) find that the resilience of European insurance companies heavily depends on product mix.

The rationale behind the diversification potential between life, non-life, and active reinsurance business with respect to the propagation of shocks emerges from the fact that all three traditional insurance activities are very different by nature. Life insurance contracts usually have a long duration with fixed annual premiums, while non-life insurance is more short-term oriented, commonly with annual renewals of contracts. Since insurance companies typically try to match the characteristics of assets and liabilities, investments of insurance companies share a similar duration with their liabilities. Reinsurance business usually captures the tail risks originating from direct insurance contracts. It can be characterized by contracts with a long-term orientation and a larger tail

[3] Note that reinsurance can be both life and non-life business.

risk. Due to the heterogeneity of underwriting risks and premium volume, reinsurers are usually able to obtain a better investment diversification by nature.

These substantial differences in insurance activities have a profound impact on the role of insurance companies as intermediaries and investors in the financial system. For example, business volatility is smaller for life insurers due to the long-term nature of their assets and liabilities in comparison to that of non-life insurers. However, this long-term nature also increases the persistence of economic shocks for life insurers regarding the overall business performance. Reinsurance in this context can be characterized by a mix between both, since it combines non-life and life insurance features. Consequently, the propagation of economic shocks from insurers to and from other financial institutions is heavily affected by the trade-off between long-term and short-term (un-)certainty about the future business development.

We extend previous studies on the role of insurance companies for financial stability and the propagation of economic shocks. Billio et al. (2012) show that the interconnectedness between insurance companies and other financial institutions has been substantially increasing during the last decades. In Section 3 we present a simple model of counterparty credit risk that is one possible source of interconnectedness. Counterparty credit risk can lead to contagion between (financial) institutions and is thus an important source for financial stability and systemic risk (Benoit et al. (2017)). The model is based on the idea that life business increases the persistence of past shocks, but decreases the future business volatility, which both determines the insurer's ability to serve a counterparty's claim. We show that the exposure of a counterparty's claim towards a stylized insurance company critically depends on the ratio between life and non-life insurance business. The model implies that a larger persistence of life business decreases the proportion of life business that minimizes counterparty exposures, since persistence decreases future expected cash flows. Moreover, a larger proportion of non-life business can reduce counterparty risk for more levered insurance companies, since counterparties are willing to exchange less volatility with a larger expected cash flow if leverage increases further.

In Section 4 we empirically test the implications of our theoretical model. For this purpose, we examine the relation between commonly used spillover risk measures and insurance business activities. We focus on the marginal expected shortfall (MES) as introduced by Acharya et al. (2016), the dependence consistent conditional Value at Risk ($\Delta\text{CoVaR}^{\leq}$) as introduced by Mainik and Schaanning (2014) and Adrian and Brunnermeier (2016), the Average Excess Conditional Shortfall Probability (CoSP) as introduced by Kubitza and Gründl (2017), and the beta-factor. We distinguish between the spillover of equity shocks to and from the global financial sector and the American non-financial sector. Our results strongly confirm the implications of our theoretical model. Life and non-life as well as assumed reinsurance and direct insurance business display significant diversification effects. Our analysis suggests that long-term bond investments of life subsidiaries are a main driver for this diversification. As such investments indicate a large persistence of life business, this finding confirms our model's intuition that persistence is a main cause for diversification between insurance lines of business.

In a similar setting but without allowing for diversification between life and non-life business, Berdin and Sottocornola (2015) find that life insurance significantly decrease financial stability, while Weiß and Mühlnickel (2014) do not find any significant contribution of life business to it. Bierth et al. (2015) examine the influence of insurers' business characteristics on financial stability and distinguish in their setting between life and non-life insurers via SIC classifications. However, they do not study differences and interactions between these two traditional insurance activities with regard to financial stability. Kaserer and Klein (2016) show as well that the impact of insurance companies on financial stability differs with the insurance business they undertake, but they neglect a diversification potential, too. We differ from these studies by allowing for an explicit potential trade-off effect between life and non-life business as motivated by our model. Previous studies about the interaction of different insurance business lines focused on the allocation of capital for a given relative size of business lines (Dhaene et al. (2012). We extend this literature by studying the relative size of business lines itself.

Moreover, our theoretical model provides an intuition for the cause of this trade-off. Thereby, we extend the literature on balance sheet contagion by providing a simple model to study the impact of persistence and volatility on counterparty credit risk. Benoit et al. (2017) provide an overview on previous studies on balance sheet contagion between financial institutions. In contrast to previous studies on network contagion, we model the balance sheet of a stylized insurance company and focus our analysis on the impact of persistence on the ability of this company to serve counterparties' claims.

The remainder of this article is structured as follows. Section 2 describes the related literature on the role of insurers for financial stability. Section 3 presents a stylized model for counterparty credit risk to an insurance group that conducts life and non-life business. In Section 4 we test the resulting theoretical implications by employing empirical measures for spillover risk. Section 5 concludes.

2 Insurance Business and Financial Stability

Although traditional insurance business is commonly not interpreted as a major source for systemic risk (International Association of Insurance Supervisors (2011), European Systemic Risk Board (2015)), there are substantial differences in the relation between insurance business activities and financial stability. For example, life insurers tend to be more vulnerable to lapse risk and hence, potentially face a higher liquidity risk (e.g. Cummins and Weiss (2014), Paulson et al. (2014)). In a scenario where a considerable number of life insurance contracts is lapsed, life insurers might also tend to fire-sale assets in response to shocks. The impact of such fire sales is controversially disputed (Geneva Association (2016)).

Due to the longer investment horizon compared to non-life insurers, possible financial guarantees and the resulting high importance of asset management, life insurers are more sensitive to market risk and interest rate risk in particular. According to the European Systemic Risk Board (2015), the scenario of a prolonged low-interest rate environment in conjunction with a drop in asset prices is considered to be one of the most destabilizing event for European life insurers and the real economy as well. Nonetheless, life insurance also stabilize future cash flows, since the underlying contracts provide long-term liquidity to the insurance company, with typical durations of more than 15 years. Thus life insurers also engage as important long-term investors for the real economy by providing funding for long-term projects (as infrastructure projects) but also for the banking sector.

In contrast, non-life insurance contracts are mainly short-term oriented contracts that provide short-term liquidity to the insurance company. On the one hand, non-life insurance business is thus more volatile than life insurance business, but on the other hand it benefits from flexible contract adjustments. Therefore, non-life insurance companies can typically react and adjust their business faster. Furthermore, non-life insurance risks are usually not correlated with the economic business cycle and financial market risks, and hence constitute a natural hedge. In contrast to life insurers, claim payments to policyholders require the occurrence of an insured event, which makes insurance runs impossible (International Association of Insurance Supervisors (2011)). Thus, liquidity risk is generally smaller than for life business.

Nevertheless, Cummins and Weiss (2014) argue that non-life insurance for individuals and smaller businesses might be difficult to substitute in the short run.[4] This difficulty in substitutability involves in particular heavily specialized lines of insurance business due to the complexity of their insurance products, e.g. medical malpractice or directors and officers liability insurance (International Association of Insurance Supervisors (2011)). Moreover, the impairment of a large non-life insurer can have a far-reaching impact on policyholders that, for example, financially depend on the insurer's payments from salary continuance policies or that require liability coverage to practice a certain profession. An example is the collapse of the Australian insurance company HIH, that lead to severe disruptions in medical services and salary payments (Autralian Government - The Treasury (2015); Wenham (2001)).

Active reinsurance business, as a third major insurance activity, differs in several ways from direct life and non-life insurance business. Reinsurance is an important and central element of insurance markets by transferring underwriting risks from a primary insurers to (one or several) reinsurers. For example, about 25 percent of U.S. property and casualty insurers have reinsurance recoverables of more than 50 percent of surplus (Cummins and Weiss (2014)). However, the economic impact of reinsurance on spillover risk is still ambiguous. On the one hand, Cummins and Weiss (2014), Park and Xi (2014) and Baluch et al. (2011) argue that reinsurance business increases interconnectedness and counterparty risk in the insurance sector. Since reinsurers usually have business relations with various primary insurers, an impairment of a reinsurer could affect many primary insurers simultaneously and thereby destabilize the financial system. On the other hand, Lelyveld et al. (2009) highlight that risks originating at reinsurers do not necessarily spill over to other sectors. Weiß and Mühlnickel (2014) find a stabilizing effect of active reinsurance for non-life insurance companies. Baur et al. (2003) highlight that reinsurers are better able to diversify and to monitor the risks they underwrite, which generally acts as a stabilizing feature of reinsurance.

[4] For example, as a reaction to the terrorist attacks on the World Trade Center on September 11th, 2001, international (re-)insurers excluded or significantly restricted terrorism coverage from insurance policies.

3 Model

3.1 Balance Sheet

The insurance company consists of two operating companies, one life and one non-life insurer. We aggregate assets and liabilities at the holding company's level since, eventually, the holding company secures the solvency and stability of the operating companies.

Asset growth per business line in year t equals the weighted average of the past asset growth in year $t-1$ and a normally distributed stochastic term. The larger the persistence, r, of the corresponding business line, the stronger is the impact of the past asset growth on the current asset growth and the smaller is its level of volatility. These dynamics are motivated by the typical asset structure of insurance companies. According to the German Insurance Association (GDV) (2016), an average life insurer in Germany held 87% in bonds and debentures and an average non-life insurer a fraction of 77% in 2015.[5]

The massive bond portfolios of life insurers typically consist of long-term bonds that are held to maturity in order to decrease the duration gap between assets and liabilities.[6] Thus, future asset returns for life and non-life insurers are mainly comprised by regular and constant coupon payments of purchased bonds. On the hand, this implies that the asset growth rate underlies a smaller volatility. On the other hand, shocks on prices or coupons that affect current reinvestments (for example resulting from a change in interest rates) have a very persistent impact on future asset returns for life insurers. Due to the difference in durations, these effects are stronger for life than for non-life business. In line with these empirical observations, we expect a larger persistence of asset growth for life insurers than for non-life insurers, $r^L > r^{NL}$. Nonetheless, we assume that both life and non-life insurers share the same asset return distribution since they belong to the same insurance group and hence are likely to share the same risk appetite.

Based on these stylized facts, the asset return is given as a modified autoregressive process. The

[5] The corresponding amounts for U.S. life insurers are 59% and for non-life insurers 53% in the first quarter of 2017 (Board of the Governors of the federal reserve system (2017)). The difference to Germany can be explained by the particularly large exposure of German life insurers to long-term contracts.

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

operating companies' assets evolve according to

$$R^L_{A,t} = r^L R_{A,t-1} + (1 - r^L)(\mu_A + \sigma_A \varepsilon^L_{A,t}) \tag{1}$$

$$R^{NL}_{A,t} = r^{NL} R_{A,t-1} + (1 - r^{NL})(\mu_A + \sigma_A \varepsilon^{NL}_{A,t}), \tag{2}$$

where $R^{()}_{A,t}$ denotes the asset growth at time t for the life (L) and non-life (NL) operating company, $r^{()} \in [0, 1]$ the level of persistence, μ_A and σ_A the mean and standard deviation of the asset growth distribution and $\varepsilon^{()}_t \sim \mathcal{N}(0, 1)$. Overall consolidated assets at the holding level at time t are given as

$$A_t = \alpha A_{t-1} R^L_{A,t} + (1 - \alpha) A_{t-1} R^{NL}_{A,t} \tag{3}$$

$$= A_{t-1} \left(\alpha R^L_{A,t} + (1 - \alpha) R^{NL}_{A,t} \right), \tag{4}$$

where α is the proportion of life business.

Underwriting business volatility is usually smaller for life insurers than for non-life insurers, since future life insurance liabilities (as for annuities or endowment life contracts) are more predictable than non-life liabilities.[7] The risks affecting the liability growth of insurance companies include mortality and longevity risks, which particularly affect life insurers, and catastrophe as well as premium and reserve risks, which particularly affect non-life insurers. Due to their long contract duration, growth of life insurance liabilities is more persistently affected by a change in the nature of these risks. Moreover, severe shocks in mortality and longevity (e.g. the outbreak of a major disease or the introduction of new medicine) are generally more persistent than the occurrence of severe catastrophes. Due to the long contract duration, a life insurer's portfolio of contracts also adjusts very slowly to such shocks and, therefore, shocks have a very persistent impact on liability growth. In contrast, non-life contracts and premiums are usually adjusted annually, which implies a fast adjustment to shocks and hence, a small persistence of liability growth.

In line with these stylized facts, the liability growth dynamics are similar to the asset growth

[7] For example, typical endowment life contracts comprise a fixed guaranteed annual return and a profit participation component that is usually adjusted annually by the insurer.

dynamics and given by

$$R_{L,t}^{L} = r^{L} R_{L,t-1} + (1 - r^{L})(\mu_L^{L} + \sigma_L^{L} \varepsilon_{L,t}^{L}) \tag{5}$$

$$R_{L,t}^{NL} = r^{NL} R_{L,t-1} + (1 - r^{NL})(\mu_L^{NL} + \sigma_L^{NL} \varepsilon_{L,t}^{NL}), \tag{6}$$

where $R_{L,t}^{()}$ denotes the liability's growth rate at time t for the life (L) and non-life (NL) operating company, $r^{()} \in [0, 1]$ the liability's growth rate's level of persistence, $\mu_L^{()}$ and $\sigma_L^{()}$ the mean and standard deviation of the liability's growth rate's distribution. Insurers typically aim for matching the duration between their assets and liabilities. Therefore, we assume that liabilities and assets exhibit the same level of persistence, r^L and r^{NL} for the life and non-life company, respectively. Since non-life and life insurance claims share little common factors, we assume that $\varepsilon_{L,t}^{L}$ and $\varepsilon_{L,t}^{NL}$ are independent. Overall liabilities at time t are given as

$$L_t = L_{t-1} \left(\alpha R_{L,t}^{L} + (1 - \alpha) R_{L,t}^{NL} \right). \tag{7}$$

The resulting equity capital at the holding company's level is then given as

$$E_t = A_t - L_t \sim \mathcal{N}(\mu_t, \sigma_t^2), \tag{8}$$

where the expected equity at time t is given as

$$\begin{aligned} \mu_t = {} & A_{t-1} \left(\alpha (r^L - r^{NL})(R_{A,t-1} - \mu_A) + r^{NL} R_{A,t-1} + (1 - r^{NL}) \mu_A \right) \\ & - L_{t-1} \left(\alpha ((r^L - r^{NL}) R_{L,t-1} + (1 - r^L) \mu_L^L - (1 - r^{NL}) \mu_L^{NL}) + r^{NL} R_{L,t-1} + (1 - r^{NL}) \mu_L^{NL} \right), \end{aligned} \tag{9}$$

and its variance at time t as

$$\begin{aligned} \sigma_t^2 = {} & A_{t-1}^2 \left(\alpha^2 (1 - r^L)^2 + (1 - \alpha)^2 (1 - r^{NL})^2 + 2 \rho \alpha (1 - \alpha)(1 - r^L)(1 - r^{NL}) \right) \sigma_A^2 \\ & + L_{t-1}^2 \left(\alpha^2 (1 - r^L)^2 (\sigma_L^L)^2 + (1 - \alpha)^2 (1 - r^{NL})^2 (\sigma_L^{NL})^2 \right). \end{aligned} \tag{10}$$

3.2 Counterparty Risk

In order to study the impact of an insurance company's business allocation on counterparty credit risk, we focus on the expected repayment of a counterparty's claim D due at time t to the insurance company. If the insurer is not able to provide sufficient funds to repay the claim, the counterparty suffers a loss. This might amplify or cause a cascade of losses of multiple financial institutions, which might result in a destabilization of financial stability. In order to approximate the insurer's sufficient funds to repay the claim D, we employ the insurer's amount of equity capital C_t as the difference between assets and liabilities at time t. For simplicity, we do not consider other financial obligations of the insurer that might increase or decrease its equity position.[8]

The expected exposure E of a counterparty to the insurance company is given as the expected loss of the counterparty. It is given by

$$E = D - \mathbb{E}\left[\min\left(D, C_t\right)\right] = (D - \mu_t)\Phi\left(\frac{D - \mu_t}{\sigma_t}\right) + \sigma_t \varphi\left(\frac{D - \mu_t}{\sigma_t}\right). \tag{11}$$

Intuitively, it is closely linked to the insurer's default risk. For $D = 0$ the expected exposure E resembles the value of a put option on the insurer's equity that pays if equity is negative, which is commonly referred to as *default put option*.[9] The more volatile the equity is, the more likely are small (negative) values and thus the more valuable is the put option and the larger is the exposure. Similarly, a small expected level of equity, $\mu_t = \mathbb{E}[C_t]$, increases the value of the put option and thereby the exposure E. The following results are based on this trade-off between the volatility and expected value of equity capital.

The derivative of the counterparty's exposure with respect to the insurer's fraction of life business, α, is given as

$$\frac{dE}{d\alpha} = -\frac{d\mu_t}{d\alpha}\Phi\left(\frac{D - \mu_t}{\sigma_t}\right) + \frac{d\sigma_t}{d\alpha}\varphi\left(\frac{D - \mu_t}{\sigma_t}\right). \tag{12}$$

The derivatives of the expected equity and its variance with respect to the fraction of life business

[8] Other obligations might reduce the available funds proportionally to γC_t, $0 < \gamma < 1$. This case would alter neither our results nor the intuition of our model.

[9] In common option pricing prices are log normally distributed. However, we would not yield a log normal (or other common probability) distribution for the equity as a sum of log normally distributed liabilities and assets. Therefore, we employ a normal distribution as an approximation. We do not expect our main results to change for a different probability distribution.

are

$$\frac{d\mu_t}{d\alpha} = A_{t-1}\left((r^L - r^{NL})R_{A,t-1} + (r^{NL} - r^L)\mu_A\right)$$
$$- L_{t-1}\left((r^L - r^{NL})R_{L,t-1} + (1 - r^L)\mu_L^L - (1 - r^{NL})\mu_L^{NL}\right) \tag{13}$$

and

$$\frac{d\sigma_t}{d\alpha} = \frac{1}{2\sigma_t}\Bigg(A_{t-1}^2 2\left(\alpha(1 - r^L) + (1 - \alpha)(1 - r^{NL})\right)(r^{NL} - r^L)\sigma_A^2 \tag{14}$$
$$+ L_{t-1}^2\left(2\alpha(1 - r^L)^2(\sigma_L^L)^2 - 2(1 - \alpha)(1 - r^{NL})^2(\sigma_L^{NL})^2\right)\Bigg).$$

Proposition 1. *If $r = r^L = r^{NL}$, $\mu_L = \mu_L^{NL} = \mu_L^L$, $\sigma_L = \sigma_L^{NL} = \sigma_L^L$, then $\alpha = 0.5$ is minimizing the counterparty's expected exposure.*
Proof: See Appendix A.

Proposition 1 is in line with intuition from standard portfolio theory suggesting that it is optimal to split investments in half if these are independent and identically distributed. This benchmark result emerges in a situation in that life and non-life business have the same levels of persistence as well as asset and liability growth rate characteristics. The following propositions study the optimal fraction of life business if, in contrast, the distributional properties differ between life and non-life business.

Proposition 2. *If only the volatility of liabilities between life and non-life business varies but $r = r^L = r^{NL}$, $\mu_L = \mu_L^{NL} = \mu_L^L$, the optimal fraction of life business is given as*

$$\alpha^* = 1 - \frac{A_{t-1}^2(1-\rho)\sigma_A^2 + L_{t-1}^2 {\sigma_L^L}^2}{2A_{t-1}^2(1-\rho)\sigma_A^2 + L_{t-1}^2\left({\sigma_L^L}^2 + {\sigma_L^{NL}}^2\right)}. \tag{15}$$

It is decreasing in higher levels of volatility of life liabilities $(\sigma_L^L)^2$, and increasing in higher levels of volatility of non-life liabilities $(\sigma_L^{NL})^2$. It is decreasing in higher levels of volatility of asset growth σ_A^2 if $\sigma_L^{NL} > \sigma_L^L$.
Proof: See Appendix A.

Propositions 1 and 2 study the optimal fraction of life business when expected asset and liability growth rates $\mu_{()}$ do not differ between life and non-life business. In this case, a change in the fraction of life business exclusively affects the volatility of the insurance company's equity, but not its expected value. While a 50% fraction is optimal if the different lines of business share the same level of volatility (as in Proposition 1), Proposition 2 shows that an increase in the asset or liability growth volatility of life (non-life) business decreases (increases) the optimal fraction of life business. Intuitively, volatility of the insurer's equity substantially impacts its ability to repay future obligations, and thus the counterparty risk of other counterparties towards the insurer. The more volatile the insurer's assets σ_A or the non-life liability growth rate σ_L^{NL} relative to the volatility of the life liabilities σ_L^{NL}, the larger is the optimal fraction of life business that minimizes the counterparty's exposure. However, if the persistence of life and non-life business differs, economic shocks have an impact on the expected equity, as the next propositions shows.

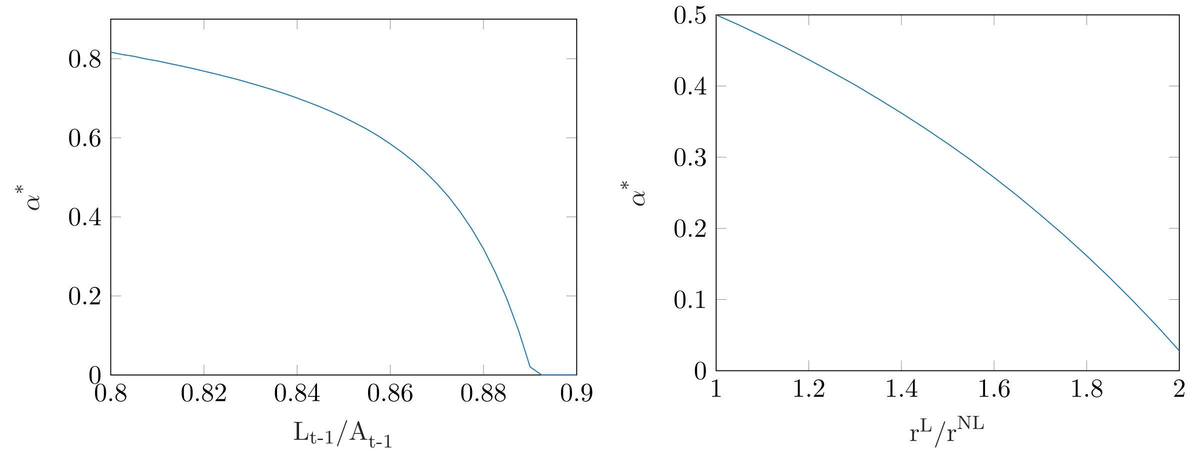
Proposition 3. *Assume that $r^L > r^{NL}$. If the previous year's liability growth rate $R_{L,t-1}$ and the size of liabilities L_{t-1} are large enough (i.e. financial distress), $\alpha^* = 0$ is optimal. If the size of liabilities L_{t-1} is sufficiently small and the asset growth rate satisfies a certain condition $R_{A,t-1} > \max(\mu_A,\, D/A_{t-1})$, counterparty's expected exposure is smaller for $\alpha = 1$ than for $\alpha = 0$.*
Proof: See Appendix A.

The last proposition shows that non-life business decreases credit counterparty risk towards insurance companies in financial distress (i.e. when liabilities are large) that face a severe liability shock. Non-life business is less persistent and thus increases the expected equity available to repay the claim in comparison to life business. But at the same time, it increases the equity's volatility as well. Furthermore, the proposition shows that during financial distress, the increase in expected equity dominates the increase in business volatility, since counterparties usually receive the remaining equity capital of the insurer in case of a insolvency. Hence, to increase the expected level of equity is more valuable than decreasing the equity's volatility in terms of minimizing the expected counterparty exposure. This behavior might be related to a kind of gambling for resurrection.

On the contrary, insurance companies with small liabilities and a sufficiently large asset growth rate are very likely to serve the claim. In such a situation, decreasing equity volatility is more valuable than increasing the expected level of equity to minimize the expected counterparty exposure. Consequently, life business is preferred over non-life business since it is associated with a smaller volatility. In this case, such a behavior is related to a kind of insuring the claim's repayment.

Figure 1 illustrates the previous findings. We also allow for different levels of volatility for life and non-life business asset growth, σ_A^L and σ_A^{NL}. We compute an economic shock in the previous year's liability and asset growth rates as the Value-at-Risk at level q of the idiosyncratic asset and liability growth rate for a 50% fraction of life business, i.e. $R_{A,t-1} = \mu_A + \frac{1}{2}(\sigma_A^L + \sigma_A^{NL})\Phi^{-1}(q)$ and $R_{L,t-1} = \mu_L + \frac{1}{2}(\sigma_L^L + \sigma_L^{NL})\Phi^{-1}(q)$. We set the Value-at-Risk level to $q = 0.05$. Our results are robust to other levels of q.

The smaller the liabilities, the larger the optimal fraction of life business, which is in line with Proposition 3. A larger persistence of life business relates to less volatility of the expected equity. Hence, an increase in persistence decreases the optimal level of life business.

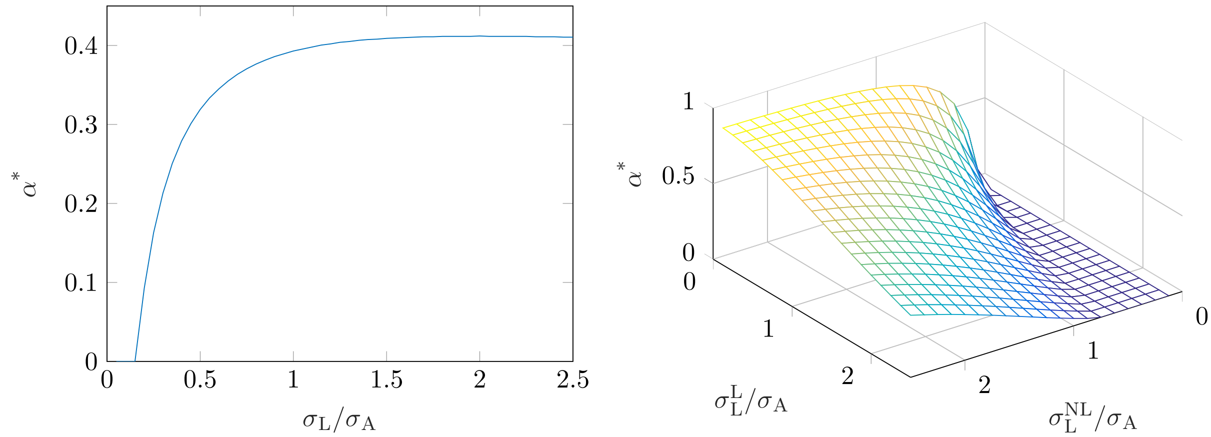


(a) Fixed persistence $r^L = 0.3$.

(b) Fixed liability size $L_{t-1} = 88$.

Figure 1: Optimal fraction of life business α for non-life persistence $r^{NL} = 0.2$, expected growth $\mu_A = \mu_L = 1.05$, underwriting volatility $\sigma_L^L = \sigma_L^{NL} = 0.01$, asset volatility $\sigma_A^L = \sigma_A^{NL} = 0.02$, and asset size $A_{t-1} = 100$.

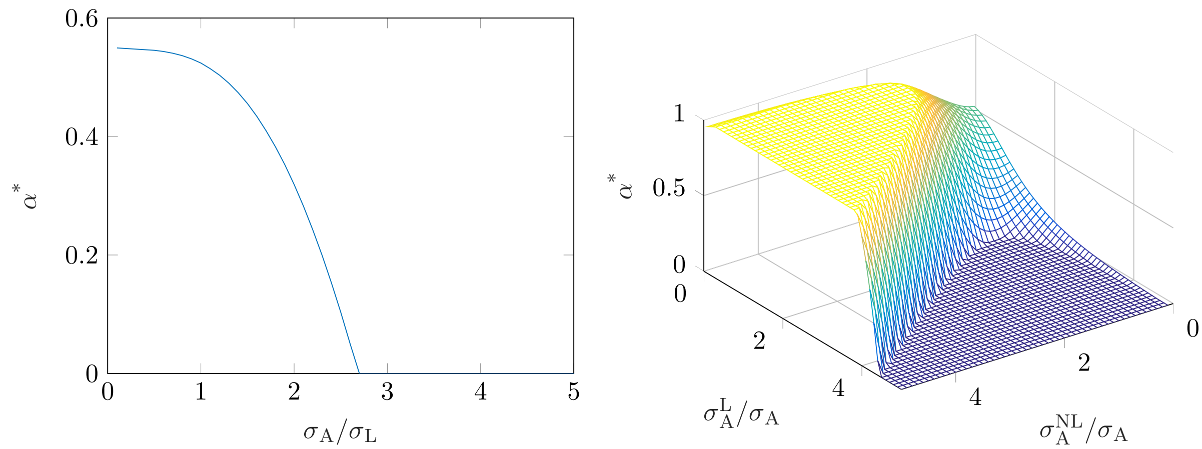
In accordance with Proposition 2, Figure 2 shows the optimal fraction of life business for different levels of liability volatility. Intuitively, the more volatile life (non-life) liabilities, the smaller (larger) the optimal fraction of life business. Similarly, Figure 3 shows that an increase in the volatility of life (non-life) asset investments is related to a decrease (increase) in the optimal fraction of life business. However, if the volatility of life (non-life) asset investments is below the volatility of non-life (life) asset investments, the optimal fraction of life business decreases (increases) again. This illustrates that too small levels of asset growth volatility can imperil the repayment of the



(a) Same level of life and non-life underwriting volatility. (b) Different levels of life and non-life underwriting volatility.

Figure 2: Optimal fraction of life business α^* for different levels of underwriting volatility for persistence $r^L = 0.3$, $r^{NL} = 0.2$, expected growth $\mu_A = \mu_L = 1.05$, asset volatility $\sigma_A^L = \sigma_A^{NL} = 0.02$, asset size $A_{t-1} = 100$, and liability size $L_{t-1} = 88$.

claim since these values diminish the insurer's chances to recover from a recent economic shock.



(a) Same level of life and non-life asset volatility. (b) Different level of life and non-life asset volatility.

Figure 3: Optimal fraction of life business α^* for different levels of asset volatility for persistence $r^L = 0.3$, $r^{NL} = 0.2$, expected growth $\mu_A = \mu_L = 1.05$, underwriting volatility $\sigma_L^L = \sigma_L^{NL} = 0.01$, asset size $A_{t-1} = 100$, and liability size $L_{t-1} = 88$.

The previous analysis shows that the fraction of life business has a substantial impact on counterparty exposures. On the one hand, the large persistence of life business can stabilize future cash flows. On the other hand, when shocks occur, less persistent non-life business provides the chance of improving future returns. This trade-off does not exclusively affect counterparty risk, but also the resilience of insurance companies in general as well as other types of business interrelations with (financial) companies.

4 Empirical Analysis

The central insight from our normative model-based analysis is, that due to differences in volatility and persistence of shocks neither conducting exclusively life nor exclusively non-life insurance business is optimal for financial stability. In contrast, the model indicates that a non-trivial proportion of life business, $0 < \alpha^* < 1$, is minimizing an insurance company's contribution to counterparty credit risk. To test this prediction in a broader perspective on financial stability, we empirically study the relation between insurance business diversification and several measures for spillover risk and financial contagion.

Life insurance activities in general relate to a larger duration of assets and liabilities and, hence, a larger persistence and smaller volatility of asset and liability growth than non-life insurance. We expect reinsurance business to be somewhere in the middle between life and non-life business. On the one hand, reinsurance contracts typically display a longer duration than non-life but smaller than life insurance contracts. On the other hand, reinsurers face larger tail risks by insuring catastrophes and extreme events. This might increase their business volatility in comparison to non-life insurers (European Commission (2002)).

4.1 Spillover measures

We distinguish spillover measures for the contribution and exposure to the risk of a system of institutions. All measures are based on equity returns. We employ the equity total return index r^I for each institution I and a value-weighted index r^S of total returns of a system. For constructing the system's index, we follow Kubitza and Gründl (2017) as described in Appendix B.1 and exclude the currently considered insurance company in order to prevent endogeneity.

As our first measure, we employ an institution's dependence-consistent $\Delta\text{CoVaR}^{\leq}$, that approximates its short-term (simultaneous) contribution to the system's tail risk. It is based on the definition of Mainik and Schaanning (2014) and Ergün and Girardi (2013) of $\Delta\text{CoVaR}^{\leq}_{S|I}$ by

$$\Delta\text{CoVaR}^{\leq}_{S|I}(q) = \text{CoVaR}_{r^I \leq VaR^I(q)}(q) - \text{CoVaR}_{\mu^I - \sigma^I \leq r^I \leq \mu^I + \sigma^I}(q) \tag{16}$$

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

$$\mathbb{P}\left(r^S \leq \text{CoVaR}_{S|I}(q) \mid r^I \leq VaR^I(q)\right) = q. \tag{17}$$

Hence, the dependence-consistent $\Delta\text{CoVaR}^{\leq}_{S|I}$ reflects the change in the system's tail risk if the institution is in distress (i.e. being in its tail). Thereby, the instituion's contribution to spillover risk is the difference between the system's VaR conditional on the instituion being in distress and the system's VaR conditional on an institution's benchmark state specified by a one-standard deviation around its mean return. By doing so, it captures the instantaneous share of a financially distressed institution in the system's financial distress, which is induced by a spillover of the institution's distress to the system. This measure is an extension of the ΔCoVaR proposed by Adrian and Brunnermeier (2016), who suggest to employ $\text{CoVaR}_{r^I = VaR^I(q)}$ instead of $\text{CoVaR}_{r^I \leq VaR^I(q)}$. Thereby, it is possible to take an institution's financial distress event beyond its VaR into account. However, Mainik and Schaanning (2014) show that the dependence-consistent CoVaR is a continuous and increasing function of the dependence between the system's and institution's return, which seems a desirable property to measure risk. Since $\Delta\text{CoVaR}^{\leq}$ is inversely related to an institution's contribution to spillover risk, we use $-\Delta\text{CoVaR}^{\leq}$ in the panel regressions. Therefore, a higher value indicates a higher contribution to spillover risk.

Kubitza and Gründl (2017) show that an institution's distress may have a persistent impact on a system, particularly in times of crises. Therefore, they suggest to aggregate the contribution to spillover risk over time. They propose to approximate the time-lagged contribution to spillover risk with the Conditional Shortfall Probability (CoSP), which is given as the likelihood of a shock in the system (i.e. the system being in its tail) τ days after an institution's distress (i.e. the institution being in its tail),

$$\psi_\tau = \mathbb{P}\left(r_\tau^S \leq VaR^S(q) \mid r_0^I \leq VaR^I(q)\right). \tag{18}$$

This definition of the CoSP allows for the interpretation that the financial distress of an institution cascades through the system over time. For an increasing time period, the institution's impact on the system vanishes.[10] The aggregation of the CoSP over a given time period yields the institution's Average Excess CoSP,

$$\overline{\psi} = \frac{1}{\tau_{\max}} \int_0^{\tau_{\max}} (\psi_\tau - q) d\tau, \tag{19}$$

which is the average excess likelihood of the system being in distress conditional on the institution's distress. We employ $\overline{\psi}$ as our second measure and interpret it as the institution's long-term contribution to spillover risk. We set the maximum considered time lag to $\tau_{\max} = 100$ days. A higher value indicates a higher contribution to spillover risk.

Both the $\Delta\text{CoVaR}^{\leq}$ and Average Excess CoSP assess how a shock spreads from one institution to a system of institutions. Although both measures refrain from specifying the transmission channel of such contagion, a prime example is counterparty risk as explained in Section 3.2. The exposure of a counterparty's claim towards the insurance company in our model reflects the insurance company's contribution to the counterparty's risk of suffering losses. Thus, it is based on the same rationale as $\Delta\text{CoVaR}^{\leq}$ and the Average Excess CoSP for the measuring of spillover risk.

In contrast to the previous measures, we employ the marginal expected shortfall (MES) as a measure of an institution's exposure to a system's distress. Acharya et al. (2016) define MES as

$$MES = -\mathbb{E}\left[r^I \mid r^S \leq VaR^S(q)\right], \tag{20}$$

which is the negative expected value of the institution's return conditional on the system being in distress. Thus, it measures the instantaneous spill over of the market's tail risk on the institution's return. Thereby, a higher value indicates a higher exposure to the system's spillover risk. MES is

[10] For a derivation the measure's statistical properties, we refer to Kubitza and Gründl (2017).

closely related to the beta-factor (Benoit et al. (2017)), since both reflect by how much a company is affected by market risk. We also include the beta factor in our analysis, as given by $\beta = \rho\sigma^I/\sigma^M$, where σ^I and σ^M are the volatility of r^I and r^S, respectively.

For all measures we employ a confidence level of $q = 5\%$, i.e. an institution's and system's stock return below the 5%-quantile of the corresponding return distribution is interpreted as financial distress in terms of a shock. The computation is based on 7-year rolling windows such that e.g. $\overline{\psi}_y$ is based on observations years $y-6, ..., y-1, y$. For MES, $\Delta\text{CoVaR}^{\leq}$ and beta we employ Maximum-Likelihood estimates and a Generalized Linear Model for $\overline{\psi}$, as suggested by Kubitza and Gründl (2017).

4.2 Data

To compute the spillover measures we rely on daily total return indices provided by *Thomson Reuters Financial Datastream*. We also include firms that are dead, but were listed in the considered estimation window. For the value-weighted indices, we consider an index for the global financial system by including all financial institutions from Datastream (FIN), as well as the Datastream index for all American non-financial companies (AMC). We account for endogeneity by excluding the currently considered insurer from the financial system's index.

Yearly firm-level data in our baseline sample is retrieved from *Thomson Reuters Worldscope*, *SNL Financial*, and *ORBIS insurance focus*. Where available, data is based on consolidated annual statements. Due to data restrictions of firm-level data, the panel is restricted to the years subsequent to (including) 2006. We employ a time-lag of one year between dependent and independent variables. Thus, the measures are computed for years 2007 to 2015. In order to mitigate currency bias, all data is collected in U.S. dollar. After matching observations by year and ISIN number, our initial sample consists of 72 insurance companies.[11] In order to study the impact of assumed reinsurance in Section 4.6, we exclude companies without any observations for premiums for assumed reinsurance. The remaining 44 companies can be found in Table 13. The proportion of long-term bond holdings for life insurance operating companies is retrieved from *A.M. Best Company*. It reflects the proportion of investments in bonds with a maturity of at least 20 years. After matching

[11] The names of the companies in the sample can be found in Table 12.

it with the baseline sample, 15 insurance companies remain in the sample.[12]

We employ gross premiums written in life business as a fraction of total gross premiums as an indicator for an insurer's engagement in life business. Note that this includes premiums for direct as well as assumed reinsurance for life business. The absolute assumed reinsurance premiums as a fraction of total gross premiums serve as an indicator for an insurer's engagement in active reinsurance business.

Since the spillover risk measures depend on equity returns, we control for an insurer's market-to-book equity value and return on equity (RoE) level as important factors for equity prices. Based on theory of stock prices, higher market-to-book and RoE ratios should indicate a higher expectation of growth rates and profitability. Thus, it should also increase the insurer's resilience towards shocks and lower its contribution and exposure to spillover risk.

These variables as well as an insurer's size and leverage are also controls for an insurer's financial situation. Previous studies emphasize that an institution's size is significantly related to its spillover risk (Berdin and Sottocornola (2015), Pankoke (2014), Weiß and Mühlnickel (2014)). Therefore, we include the logarithm of the insurer's total assets as a measure for size. The evidence on the relation of an insurance company's leverage to financial stability is mixed. In general, leverage in insurance is substantially different to that of banks due to the quasi-absence of debt (Thimann (2014)). Nevertheless, Harrington (2009) and Chen et al. (2013) show that highly levered life insurance companies tend to be more vulnerable to economic shocks. In line with our model, we employ the ratio of total assets to the book value of equity as measure for leverage. By including year fixed effects, we capture changes in the market as well as in the regulatory environment.

Descriptive statistics are reported in Table 1. The mean values of the Average excess CoSP in our sample are 5.4 % and 5.5 % regarding the global financial and the American non-financial market, respectively. This means that an average insurer in our sample increases the average likelihood of a market's shock within 100 days after the institution's shock by 5.4 % (FIN) and 5.5 % (AMC), respectively. Regarding the $\Delta\text{CoVaR}^{\leq}$, an average insurer increases the system's loss by about 3.7 % (FIN) and 3.8 % (AMC) during the days on which the institution was in distress (i.e. being in its tail). The average values for MES correspond to an institution's loss on its stock return of about 3.1 % (FIN) and 3.0 % (AMC) simultaneously to the days on which the respective

[12]The names of the companies in the sample can be found in Table 14.

market was in distress. Overall, the average values for MES and $\Delta\text{CoVaR}^{\leq}$ are slightly larger than the values for MES and ΔCoVaR in Bierth et al. (2015), who examine a larger time period, and slightly smaller than in Weiß and Mühlnickel (2014), who solely examine the 2007-08 financial crisis. Considering the average values of the beta-factor, they indicate that the average insurer's stock performance is less volatile than the market.

Statistic	N	Mean	St. Dev.	Min	Max
Average Excess CoSP ($\bar{\psi}$) (FIN)	517	0.054	0.022	0.001	0.118
Average Excess CoSP ($\bar{\psi}$) (AMC)	516	0.055	0.022	0.001	0.115
- $\Delta\text{CoVaR}^{\leq}$ (FIN)	517	0.037	0.009	0.008	0.047
- $\Delta\text{CoVaR}^{\leq}$ (AMC)	516	0.038	0.013	0.004	0.053
MES (FIN)	517	0.031	0.017	0.002	0.093
MES (AMC)	516	0.030	0.020	0.001	0.106
beta (FIN)	517	0.992	0.471	0.190	2.646
beta (AMC)	516	0.881	0.526	0.103	2.806
Market Cap (in million)	517	11,650	15,309	328	97,086
Premiums Life	517	0.443	0.396	0.000	1.000
Reinsurance assumed	324	0.169	0.297	0.000	1.000
Log (Total Assets in thd)	517	17.815	1.439	13.805	21.554
Market-to-Book	517	1.323	0.698	0.192	4.022
RoE	517	0.096	0.109	−1.014	0.374
Leverage	517	10.774	6.804	1.582	39.014
Long-Term Bonds	118	58.326	20.919	18.000	95.900

Table 1: Descriptive statistics for spillover measures and company variables in the years 2007 to 2015 based on insurer-year observations, including the global financial (FIN), and American non-financial (AMC) sector. Source: *Thomson Reuters Worldscope*, *SNL Financial*, *ORBIS insurance focus*, *A.M. Best Company* and own calculations.

The ratios of life and non-life business of the average insurer in our sample are 44.3 % and 55.7 %, respectively. This indicates that on average, insurers in our sample are more focused on non-life business than on life business. Considering the sub-sample with observations for reinsurance, the average insurer assumed reinsurance on a level of 16.9 % regarding total premiums. These reinsurance premiums can be collected for both, life and non-life business, but indicate that the sub-sample consists mainly of pure direct insurers. The insurers' market capitalization in the entire sample ranges from 328 million U.S. dollar to 97.09 bn U.S. dollar, whereof the average insurer has a market capitalization of about 11.65 bn U.S. dollar. Since we use the logarithm of total assets as a measure for the insurer's size, the average insurer has a size of 54.57 bn U.S. dollar and the entire band ranges from 0.99 bn U.S. dollar to 2,295 bn U.S. dollar. The mean value is in line with the results of Bierth et al. (2015) and Weiß and Mühlnickel (2014). The insurers have on average a Market-to-Book ratio of 1.32, a return on equity of about 9.6 % and a leverage ratio of 10.8. These values are again in line with those given by Bierth et al. (2015) and Weiß and Mühlnickel (2014), who show only slighty larger Market-to-Book ratios and return on equity values. Long-term bond investments amount to an average fraction of 58.33 % to total investments for the corresponding subsample, which underpins the general long-term investment behavior of insurance companies. The geographical distribution of the 72 insurers in our sample shows that 46 % correspond to insurers from Europe, 38 % to North America (U.S. and Canada), 8 % to ASIA, 7 % to Africa and 1 % to Australia. Regarding Europe, the majority with six insurers is located in Switzerland, followed by Italy with five and Germany with four insurers. Overall, only two insurers of our sample (AIG and Lincoln National Corp.) got financial aid from government during the financial crisis.

4.3 Life Business

Based on the intuition from the previous section, we compute the relation between the propoertion of life business and spillover risk measures in the following baseline OLS panel regression

$$Y_{i,t} = \beta_0 + \beta_{life,1} life_{i,t}^2 + \beta_{life,2} life_{i,t} + \beta_C C_{i,t-\tau} + \beta_t + \varepsilon_{i,t} \quad (21)$$

for insurer i and year t. $Y_{i,t}$ is the respective spillover measure with respect to the global financial or American non-financial sector. $life_{i,t}$ refers to the insurer's fraction of gross life premiums to total gross premiums, and C to the insurer's control variables as log total assets, market-to-book ratio, return on equity, and leverage. The squared term of the life business ratio is introduced to test for a potential nonlinear u-shaped relationship between life insurance business and spillover risk. We include time-fixed effects β_t and compute insurer-clustered standard errors.

The results are presented in Tables 2 and 3. Taking both life insurance coefficients into consideration, life insurance business is basically positively related to all spillover measures and to the beta-factor. Thus, an increase in life business is related to an increase in the insurer's likelihood to cause the markets' subsequent tail returns within 100 days after its own shock, as well as its contribution and exposure to the markets' tail risk. Furthermore, since the coefficients are significant regarding all measures on both markets, it indicates that an u-shaped relation between life business and spillover risk exists, which gives the foundation for a diversification effect to emerge. The relation of our control variables with the spillover 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 tends to be positively related, whereas market to book, return on equity and leverage are negatively related to spillover risk.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Life^2)	0.800***	0.317**	1.180***	1.140***
	(0.260)	(0.146)	(0.369)	(0.344)
Premiums.Life	−0.874***	−0.317*	−0.968**	−0.972***
	(0.288)	(0.171)	(0.386)	(0.368)
Log.Total.Assets	0.017	0.031***	0.070**	0.092***
	(0.018)	(0.009)	(0.028)	(0.027)
Market.to.Book	−0.044	−0.046*	−0.159**	−0.167**
	(0.032)	(0.024)	(0.071)	(0.067)
RoE	−0.149	−0.043	−1.334***	−1.026**
	(0.299)	(0.073)	(0.505)	(0.478)
Leverage	0.0002	−0.003	0.0003	−0.001
	(0.004)	(0.002)	(0.007)	(0.006)
Constant	0.428	0.026	−0.312	−0.430
	(0.286)	(0.153)	(0.475)	(0.447)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	53.2	−554	439.4	374.6
Observations	517	517	517	517
R^2	0.565	0.624	0.422	0.379
Adjusted R^2	0.553	0.614	0.406	0.362
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2: Baseline OLS Regression for Insurance Business: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities. All spillover measures are standardized. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	0.961***	0.702***	2.019***	1.981***
	(0.256)	(0.221)	(0.396)	(0.402)
Premiums.Life	−1.012***	−0.736***	−1.783***	−1.790***
	(0.285)	(0.263)	(0.407)	(0.413)
Log.Total.Assets	0.025	0.075***	0.070*	0.093***
	(0.018)	(0.014)	(0.036)	(0.035)
Market.to.Book	−0.059*	−0.074*	−0.183**	−0.198**
	(0.034)	(0.039)	(0.093)	(0.089)
RoE	−0.080	−0.093	−1.511**	−1.058*
	(0.289)	(0.147)	(0.633)	(0.559)
Leverage	−0.001	−0.010***	−0.005	−0.010
	(0.004)	(0.004)	(0.008)	(0.008)
Constant	0.281	−0.666***	−0.244	−0.427
	(0.293)	(0.233)	(0.646)	(0.621)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	37.9	−111.6	587.4	550
Observations	516	516	516	516
R^2	0.557	0.560	0.434	0.390
Adjusted R^2	0.544	0.548	0.418	0.373
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 3: Baseline OLS Regression for Insurance Business: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

The optimal fraction of life business that minimizes the respective spillover measures results from the first-order-condition with respect to the relative size of life premiums in Regression 21,

$$\alpha^* = -\frac{\beta_{life,2}}{2\beta_{life,1}}. \tag{22}$$

For all measures we find a significant and convex u-shaped relationship between life business and spillover risk, as $\beta_{life,1} > 0$ and $\beta_{life,2} < 0$. In Table 4 we report the resulting optimal fractions of life business α^*. There is a clear ranking of α^* with respect to the spillover measures. In line with our intuition and the theoretical model, measures for the contribution to spillover risk (Average Excess CoSP and ΔCoVaR$^{\leq}$) are associated with a larger optimal fraction of life business (roughly 54% and 51%, respectively) than measures for the exposure to spillover risk (MES and beta; roughly 42% and 44%, respectively). Differences between the global financial and American non-financial market are negligible, which adds to the robustness of our result.

Spillover Measure	FIN	AMC
Average Excess CoSP	0.55	0.53
ΔCoVaR$^{\leq}$	0.50	0.52
MES	0.41	0.44
beta	0.43	0.45

Table 4: Optimal fraction of life premiums α^* implied by panel regression with respect to the global financial and American non-financial sector.

Interestingly, the fraction of life business that minimizes spillover risk varies between the measures. It is clearly larger for measures for the contribution to spillover risk (as the Average Excess CoSP and ΔCoVaR$^{\leq}$) than for measures for the exposure to spillover risk (as MES and beta). This indicates that non-life insurance business is more beneficial for decreasing an insurance company's exposure to a system's risk, but not for its contribution to it. This finding is in line with our model in Section 3. In contrast to a counterparty's exposure, that resembles a put option, the shareholder value of a company mirrors a call option, $V = \mathbb{E}[\max(C_t, 0)]$, where C_t is the expected equity value at time t. This option increases with the expected equity and its volatility. In our model, upon a shock, both the equity's mean and volatility increase with non-life insurance activities, since these are less persistent and more volatile than life activities. Consequently, the shareholder value is larger for a higher level of non-life business. As MES and beta reflect the average change in the company's shareholder value (i.e. in equity returns) upon a market shock, a higher fraction of non-life business minimizes these measures compared to measures for the contribution to spillover risk (as ΔCoVaR$^{\leq}$ and the Average Excess CoSP).

Our empirical findings confirms our theoretical model's intuition that life insurance activities do not in general increase spillover risk. In contrast, a mix of life and non-life business is able to diversify spillover risk. Then, an insurer's contribution and exposure to spillover risk benefits from diversification of persistence of economic shocks and volatility.

In addition to the intuition of our model, business characteristics other than persistence and volatility might impact diversification between life and non-life business. As discussed in Section 2, life and non-life activities differ in several other ways that are not incorporated in our model of counterparty risk. For example, life insurance is subject to a potentially larger liquidity risk than non-life insurance, while non-life insurers might be more difficult to substitute in the short run. These risks might add to the interaction between life and non-life insurance. Nonetheless, in the following section we show that persistence of business activities is indeed significantly related to the diversification of life and non-life insurance activities with respect to financial stability.

4.4 Persistence

Our theoretical model suggests that the optimal fraction of life business that minimizes spillover risk decreases with the persistence of life business. The intuition is that with a larger persistence of life business, less life business is necessary to reach an optimal level of diversification. This result is at the core of our model and suggests that persistence is a main driver for the trade-off between life and non-life business with respect to counterparty risk.

To proxy the persistence of life business, we employ the fraction of life insurers' investments in long-term bonds (i.e. bonds with a maturity of at least 20 years) as provided by AM Best for US life insurance companies.[13] Bonds are the most common asset class in an insurer's asset portfolio and are typically held until maturity. Thus, a large proportion of long-term bonds indicates a

[13] In case AM Best reports the proportion of long-term bond investments for different life subsidiaries of the same insurance group, we employ the mean value in the regression. However, our results do not change when employing the maximum or minimum value.

large asset duration. Since life insurers aim for matching durations of assets and liabilities, asset duration reflects the duration of an insurer's liabilities. In line with the intuition developed in Section 3, a large asset or liability duration is related to a large persistence of asset or liability growth, respectively.[14]

We interact long-term bond investments with the proportion of life business in order to test for an impact of persistence on the diversification between life and non-life business. The regression model is given as[15]

$$\begin{aligned} Y_{i,t} =& \beta_0 + \beta_{life,1} life_{i,t}^2 + \beta_{life,LTBonds,1} life_{i,t}^2 * LTBonds_{i,t} + \beta_{life,2} life_{i,t} \\ &+ \beta_{life,LTBonds,2} life_{i,t} * LTBonds_{i,t} + \beta_{LTBonds} LTBonds_{i,t} \\ &+ \beta_{lev} leverage + \beta_C C_{i,t-\tau} + \beta_t + \varepsilon_{i,t}. \end{aligned} \tag{23}$$

where $LTBonds_{i,t}$ is the fraction of long-term bonds to total investments of insurer i at time t. The results can be found in Appendix B.3 in Tables 16 and 17. As expected, long-term bond investments have a significant impact on most spillover risk measures. Based on this regression model, the ratio of life business that minimizes the respective risk measure is given as

$$\alpha^* = -\frac{\beta_{life,2} + \beta_{life,LTBonds,2} LTBonds}{2(\beta_{life,1} + \beta_{life,LTBonds,1} LTBonds)}. \tag{24}$$

The optimal ratio of life business, α^*, is then decreasing with investments in long-term bonds if its derivative is negative,

$$\frac{d\alpha^*}{dLTBonds} = \frac{\beta_{life,LTBonds,1}\beta_{life,2} - \beta_{life,LTBonds,2}\beta_{life,1}}{2(\beta_{life,1} + \beta_{life,LTBonds,1} LTBonds)^2} < 0. \tag{25}$$

Table 5 reports the derivative (in hundreds) of Equation (25) for the median level of long-term bond investments as in our sample (which roughly equals 58.6%). The results confirm the implications of the theoretical model in Section 3 that an insurance company's optimal fraction of life business that minimizes spillover risk is smaller for more persistent life business. This finding

[14] Due to data limitations, our sample shrinks to 15 insurance companies in this analysis. These are reported in Table 14. The other independent variables' empirical distributions in this subsample match the empirical distributions of the entire baseline sample.

[15] An unreported regression in that we interact long-term bond investments only with the linear term of life business yields very inconclusive results. Therefore, we interact it with both life terms.

is particularly strong for the global financial market.

The difference in our finding between the financial and non-financial sector can be explained by the different role of insurers for these sectors. Since insurers are important counterparties for transactions in the financial sector, counterparty credit risk towards insurers plays an important role for financial stability, which is at the core of our model. Insurers directly engage with the non-financial sector mainly by providing actual insurance coverage and investing. For this business, counterparty credit risk is far less important than the long-term stability of cash-flows. Consequently, with respect to the stability of non-financial markets a smaller (or no) increase in non-life business is optimal upon an increase in the persistence of life business.

Spillover Measure	FIN	AMC
Average Excess CoSP	-0.29	-0.05
$\Delta\text{CoVaR}^{\leq}$	-0.01	0.03
MES	-0.27	-0.11
beta	-0.23	-0.09

Table 5: First derivatve (in hundreds) of the optimal fraction of life premiums α^* with respect to fraction of long-term bonds as implied by panel regression (24), regarding the global financial (FIN) and American non-financial sector (AMC) for the median level of long-term bond investments in our sample (58.6%). If the reported number is negative, α^* is decreasing with the fraction of long-term bonds (persistence).

In an unreported regression we perform the same analysis with the proportion of long-term investments on the level of the insurance group. In contrast to the previous findings, neither is the interaction between long-term investments and life business significant, nor does the optimal proportion of life business decrease with long-term investments. This result is again in line with our model that does not imply an effect of the group's level of business persistence, but an effect of different levels of persistence between life and non-life business.

4.5 Leverage

Our theoretical model suggests that a smaller ratio of life business minimizes counterparty risk for a highly levered insurance company. The intuition is that a decrease in volatility, as it is associated with more life business, becomes less important than an increase in expected equity, as it is associated with more non-life business, the less likely the repayment of a claim is. We test this hypothesis by interacting leverage and life business in the following regression

$$\begin{aligned} Y_{i,t} =& \beta_0 + \beta_{life,1} life_{i,t}^2 + \beta_{life,2} life_{i,t} + \beta_{life,lev,2} life_{i,t} * leverage_{i,t} \\ &+ \beta_{lev} leverage_{i,t} + \beta_C C_{i,t-\tau} + \beta_t + \varepsilon_{i,t}. \end{aligned} \tag{26}$$

The results can be found in Appendix B.3 in Tables 18 and 19. The optimal ratio of life business that minimizes the respective risk measure is given as

$$\alpha^* = -\frac{\beta_{life,2} + \beta_{life,lev,2} leverage}{2\beta_{life,1}}. \tag{27}$$

Table 6 reports α^* for an insurer with either very low or high leverage (as given by the minimum or maximum leverage ratio observed in our sample, respectively).

Spillover Measure	FIN (low lev.)	AMC (low lev.)	FIN (high lev.)	AMC (high lev.)
Average Excess CoSP	0.61	0.56	0.30	0.40
ΔCoVaR$^{\leq}$	0.53	0.50	0.38	0.63
MES	0.39	0.42	0.53	0.58
beta	0.41	0.43	0.57	0.60

Table 6: Optimal fraction of life premiums α^* implied by panel regression (26) if leverage is either low (as given by the minimum observed leverage ratio in our sample) or high (as given by the maximum observed leverage ratio in our sample) regarding the global financial and American non-financial sector.

As implied by our model, the optimal ratio of life business is smaller for highly levered insurers with respect to the two measures for the contribution to spillover risk, the Average Excess CoSP and ΔCoVaR. This result is in line with the rationale that high leverage increases the probability of not being able to serve claims. In this case, the more volatile and less persistent non-life business reduces counterparty risk by increasing expected future cash flows. We do not find the interaction between life business leverage to be significant in the regression. However, the difference in the optimal ratio for the least and most levered insurer is 31% (16%) for the Average Excess CoSP with respect to the global financial sector (American non-financial sector), and 15% for the dependence-consistent

ΔCoVaR$^{\leq}$ with respect to the global financial sector, and thereby economically significant.

Our finding is in line with our model from Section 3, where leverage impacts the counterparty exposure to an insurer and, thereby, its contribution to spillover risk. As we discuss in Section 3 and particularly in Proposition 3, leverage decreases the likelihood that counterparties' claims are fully paid. Thereby, from a counterparty's perspective, leverage shifts weight from the volatility of equity to expected equity. Since expected equity is increasing with non-life business, the optimal fraction of life business decreases with leverage. In contrast, Table 6 indicates that the measures for an insurer's exposure to spillovers, the marginal expected shortfall (MES) and beta, are related to a larger optimal ratio of life business. Again, this confirms the intuition that counterparty credit risk in our model is reflected by spillover measures for the contribution but not necessarily exposure to economic shocks. In contrast, the exposure to economic shocks might be driven by other factors, in particularly the level of systematic exposure of business activities.

4.6 Reinsurance Business

For reinsurance business we do not find a significant u-shaped relation with spillover measures.[16] This finding suggests that assumed (i.e. active) reinsurance business and direct insurance business does not have a diversification effect similar to non-life and life business. This result is not surprising, considering that direct insurance and reinsurance liabilities are strongly correlated - in contrast to life and non-life liabilities, which are usually very loosely correlated. Therefore, there is no apparent diversification benefit between direct insurance and reinsurance business.

However, given that reinsurance, non-life, and life business have different business characteristics, we expect a diversification effect between the three. In particular, reinsurance tends to be more persistent but also exposed to larger tail risks than non-life business. On the one hand, this might decrease the optimal fraction of life business, since shocks are rather persistent already. On the other hand, reinsurance might increase the optimal fraction of life business to account for the higher level of volatility.

In order to examine the impact of reinsurance, we interact life business with reinsurance business

[16] Tables 21 and 20 in Appendix B.3 report the results of the OLS regression

$$Y_{i,t} = \beta_0 + \beta_{reins,1} reins_{i,t}^2 + \beta_{reins,2} reins_{i,t} + \beta_C C_{i,t-\tau} + \beta_t + \varepsilon_{i,t}. \tag{28}$$

We do not find that $\beta_{reins,2}$ is in general significantly different from zero.

in the following regression model

$$Y_{i,t} = \beta_0 + \beta_{life,1} life^2_{i,t} + \beta_{life,2} life_{i,t} + \beta_{life,reins,2} life_{i,t} * reinsurance_{i,t} + \beta_{reins} reins_{i,t} + \beta_C C_{i,t-\tau} + \beta_t + \varepsilon_{i,t}. \quad (29)$$

The results can be found in Tables 8 and 7. Although we do not find a significant interaction between reinsurance, life, and non-life business, we find that reinsurance tends to increase diversification benefits of life insurance business as $\beta_{life,reins,2}$ is negative.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	0.686**	0.148	0.985**	0.921*
	(0.347)	(0.174)	(0.491)	(0.471)
Premiums.Life	−0.597	−0.096	−0.320	−0.388
	(0.429)	(0.232)	(0.601)	(0.565)
Reinsurance.assumed	0.113	0.044	0.014	0.069
	(0.141)	(0.050)	(0.215)	(0.208)
Log.Total.Assets	0.038	0.027***	0.055	0.077*
	(0.025)	(0.010)	(0.045)	(0.041)
Market.to.Book	−0.018	−0.015	−0.110	−0.106
	(0.066)	(0.025)	(0.148)	(0.136)
RoE	−0.358	−0.056	−1.382***	−1.131**
	(0.278)	(0.079)	(0.485)	(0.447)
Leverage	−0.010	−0.003	−0.012	−0.010
	(0.009)	(0.003)	(0.016)	(0.014)
Premiums.Life:Reinsurance.assumed	−0.139	−0.053	−0.508	−0.455
	(0.186)	(0.060)	(0.412)	(0.368)
Constant	−0.001	−0.011	−0.102	−0.243
	(0.430)	(0.170)	(0.761)	(0.673)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	80.3	−415.9	264.6	239.2
Observations	324	324	324	324
R^2	0.520	0.627	0.465	0.389
Adjusted R^2	0.495	0.607	0.437	0.357
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Baseline OLS Regression for Insurance and Reinsurance Business: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

In Table 9 we compare the optimal fraction of life insurance for a direct insurer without any assumed reinsurance with that for a pure reinsurance company without any direct insurance business. The optimal fraction of life insurance business is larger for a pure reinsurer for all spillover

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	0.881***	0.554**	2.074***	2.117***
	(0.337)	(0.277)	(0.615)	(0.619)
Premiums.Life	−0.803*	−0.522	−1.514**	−1.674**
	(0.429)	(0.346)	(0.749)	(0.708)
Reinsurance.assumed	0.074	0.172	0.044	0.076
	(0.150)	(0.137)	(0.244)	(0.234)
Log.Total.Assets	0.046*	0.070***	0.043	0.060
	(0.025)	(0.017)	(0.053)	(0.049)
Market.to.Book	−0.049	−0.090*	−0.196	−0.198
	(0.074)	(0.048)	(0.189)	(0.177)
RoE	−0.283	−0.198	−1.582***	−1.155**
	(0.269)	(0.134)	(0.570)	(0.472)
Leverage	−0.009	−0.007	−0.006	−0.005
	(0.010)	(0.005)	(0.021)	(0.019)
Premiums.Life:Reinsurance.assumed	−0.041	−0.179	−0.413	−0.342
	(0.194)	(0.143)	(0.526)	(0.475)
Constant	−0.140	−0.642**	0.206	0.037
	(0.435)	(0.277)	(0.941)	(0.853)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	62.5	−112.2	384.1	342.3
Observations	324	324	324	324
R^2	0.523	0.579	0.458	0.423
Adjusted R^2	0.499	0.557	0.430	0.393
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8: Baseline OLS Regression for Insurance and Reinsurance Business: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

measures and sectors. This finding suggests that the larger tail risk of reinsurance business dominates potential positive effects from more long-term oriented business of reinsurance with respect to financial stability. The larger tail risk can be diversified in terms of spillover risk by assuming more life business in order to decrease overall business volatility.

Spillover Measure	FIN (direct)	AMC (direct)	FIN (reins.)	AMC (reins.)
Average Excess CoSP	0.44	0.46	0.54	0.48
$\Delta\text{CoVaR}^{\leq}$	0.33	0.47	0.50	0.63
MES	0.16	0.36	0.42	0.46
beta	0.21	0.40	0.46	0.48

Table 9: Optimal fraction of life premiums α^* for direct insurers (no reinsurance assumed) and reinsurers (no direct insurance) implied by panel regression with respect to the global financial and American non-financial sector.

4.7 Robustness Checks

We examine the robustness of our findings by employing several other model specifications. The results are available from the authors upon request.

First, we change the time-lag between dependent and independent variables from one year to two years. This decreases the number of observations. However, the main findings remain the same. Second, we employ an additional model set-up for the regression analysis, namely generalized linear models (GLMs) with logarithmic link-function and either normally distributed errors. The general results remain the same and can be found in Tables 22 and 23 in Appendix B.3. Results of a GLM for other regressions as well as a GLM with gamma distributed errors also provide the same main results and are available on request by the authors.

Third, to assess the robustness of our finding of Section 4.5 which shows that leverage decreases the optimal ratio of life business, we also interact the quadratic term of the relative size of life business with an insurer's leverage in the following model

$$\begin{aligned} Y_{i,t} =& \beta_0 + \beta_{life,1} life_{i,t}^2 + \beta_{life,lev,1} life_{i,t}^2 * leverage + \beta_{life,2} life_{i,t} \\ &+ \beta_{life,lev,2} life_{i,t} * leverage_{i,t} + \beta_{lev} leverage_{i,t} + \beta_C C_{i,t-\tau} + \beta_t + \varepsilon_{i,t}. \end{aligned} \tag{30}$$

The results can be found in Appendix B.3 in Tables 25 and 24. In this model, the ratio of life business that minimizes the respective risk measure is given as

$$\alpha^* = -\frac{\beta_{life,2} + \beta_{life,lev,2} leverage}{2(\beta_{life,1} + \beta_{life,lev,1} leverage)}. \tag{31}$$

The optimal ratio of life business, α^*, is decreasing with leverage if

$$\frac{d\alpha^*}{dleverage} = \frac{\beta_{life,lev,1}\beta_{life,2} - \beta_{life,lev,2}\beta_{life,1}}{2(\beta_{life,1} + \beta_{life,lev,1} leverage)^2} < 0. \tag{32}$$

Table 10 reports the derivative (in hundreds) as from Equation (32) for the median level of leverage (808%) in our sample. A positive value relates to an increase in the optimal ratio of life business for increasing leverage. The results confirm our findings from the theoretical model in Section 3 and the previous empirical analysis in Section 4.5 that leverage decreases the fraction of life insurance business that minimizing an insurer's contribution to spillover risk, but not its exposure.

Spillover Measure	FIN	AMC
Average Excess CoSP	-0.70	-0.38
ΔCoVaR$^{\leq}$	-0.14	0.29
MES	1.84	1.57
beta	1.54	1.44

Table 10: First derivatve (in hundreds) of the optimal fraction of life premiums α^* with respect to leverage as implied by panel regression (31), with respect to the global financial (FIN) and American non-financial sector (AMC) for the median level of leverage in our sample (808%). If the reported number is negative, α^* is decreasing with leverage.

To assess the robustness of our finding of Section 4.6 that assumed reinsurance increases the optimal ratio of life business, we also interact the quadratic term of the relative size of life business with the relative size of the assumed reinsurance business in the following model

$$\begin{aligned} Y_{i,t} =& \beta_0 + \beta_{life,1} life_{i,t}^2 + \beta_{life,reins,1} life_{i,t} * reins_{i,t} + \beta_{life,2} life_{i,t} \\ &+ \beta_{life,reins,2} life_{i,t} * reins_{i,t} + \beta_{lev} leverage_{i,t} + \beta_C C_{i,t-\tau} + \beta_t + \varepsilon_{i,t}. \end{aligned} \tag{33}$$

The results can be found in Appendix B.3 in Tables 27 and 26. Analogously to the former analysis, the ratio of life business that minimizes the respective risk measure is given as

$$\alpha^* = -\frac{\beta_{life,2} + \beta_{life,reins,2} reins}{2(\beta_{life,1} + \beta_{life,reins,1} reins)}. \tag{34}$$

The optimal ratio of life business, α^*, is increasing with reinsurance if

$$\frac{d\alpha^*}{dreins} = \frac{\beta_{life,lev,1}\beta_{life,2} - \beta_{life,lev,2}\beta_{life,1}}{2(\beta_{life,1} + \beta_{life,lev,1} reins)^2} > 0. \tag{35}$$

Table 11 reports the derivative (in hundreds) from Equation (35) for the median fraction of reinsurance business (3%) in our sample. A positive value relates to an increase in the optimal ratio of life business for an increasing fraction of reinsurance business. The results confirm our findings from the previous empirical analysis in Section 4.6 that an insurance company's optimal fraction of life business tends to increase with assumed reinsurance business with respect to the insurance company's contribution and exposure to spillover risk.

Spillover Measure	FIN	AMC
Average Excess CoSP	4.70	4.30
ΔCoVaR$^{\leq}$	-31.58	16.76
MES	7.16	8.19
beta	-7.14	4.31

Table 11: First derivative (in hundreds) of the optimal fraction of life premiums α^* with respect to assumed reinsurance business as implied by panel regression (34), with respect to the global financial (FIN) and American non-financial sector (AMC) for the median ratio of assumed reinsurance business in our sample (3%). If the reported number is positive, α^* is increasing with reinsurance.

5 Conclusion

In this article we examine the relation between diversification of insurance business activities and financial stability. For this purpose, we develop a theoretical balance sheet model of an insurance group to examine the diversification potential between life and non-life insurance for counterparty credit risk exposure. The model implies that diversification between life and non-life business decreases counterparty exposures. This results from the stylized fact that life business is more persistent but less volatile than non-life business.

We employ spillover risk measures in order to empirically test the implications of our model. The empirical analysis confirms the intuition from our model that the interaction between persistence and volatility of life and non-life business has a significant and strong impact on the contribution of insurance companies to the global financial system's as well as the American non-financial system's risk. The diversification potential arising from this interaction is less pronounced for the exposure of insurance companies to a system's risk. An intuitive reason is that measures for exposure are related to the shareholder value, which is increasing with volatility.

Overall, our findings contribute to a more detailed understanding of the spillover risk related to insurance companies' business activities. In particular, they argue in favor of an activity-based macro-prudential regulation approach and might also have practical implications for a re-evaluation of the IAIS indicator-based model (International Association of Insurance Supervisors (2016)). Our results suggest that an activity-based regulation should acknowledge the differences in persistence of insurance activities and the resulting risk diversifying effect. In this sense, a regulatory approach might not generally penalize certain activities (as life insurance) but missing diversification between insurance activities.

Finally, our results carry over to other institutions that engage in activities with different levels of persistence. In the most general sense, we find that financial stability is not generally positively related to the volatility of business activities, but volatility can also be a chance to recover faster from past shocks.

A Proofs

Proposition 1. *If* $r = r^L = r^{NL}$, $\mu_L = \mu_L^{NL} = \mu_L^L$, $\sigma_L = \sigma_L^{NL} = \sigma_L^L$, *then* $\alpha = 0.5$ *is minimizing the counterparty's expected exposure.*

Proof. Under the conditions above, expected equity capital is equal to

$$\mu_t = A_{t-1}(\mu_A + r(R_{A,t-1} - \mu_A)) - L_{t-1}(\mu_L + r(R_{L,t-1} - \mu_L)), \tag{36}$$

which is independent from α. The variance of equity is equal to

$$\begin{aligned}\sigma_t^2 = {} & A_{t-1}^2 \left(\alpha^2(1-r)^2(\sigma_A)^2 + (1-\alpha)^2(1-r)^2(\sigma_A)^2 + 2\rho\alpha(1-\alpha)(1-r)^2)\sigma_A^2\right) \\ & + L_{t-1}^2(1-r)^2\sigma_L^2\left(\alpha^2 + (1-\alpha)^2\right),\end{aligned} \tag{37}$$

which is dependent from α. Thus, the marginal expected exposure from equation 12 is given as

$$\frac{dE}{d\alpha} = \frac{d\sigma_t}{d\alpha}\varphi\left(\frac{D-\mu_t}{\sigma_t}\right). \tag{38}$$

Since $\varphi > 0$, the first-order-condition for an optimal fraction of life business α is $\frac{dE}{d\alpha} = 0$, which is equivalent to

$$\frac{d\sigma_t}{d\alpha} = 0. \tag{39}$$

Since $\frac{d\sigma_t}{d\alpha} = \frac{1}{2}\sigma_t^{-1}\frac{d\sigma_t^2}{d\alpha}$ it is sufficient that $\frac{d\sigma_t^2}{d\alpha} = 0$, which is equivalent to

$$A_{t-1}^2\left[(1-r)^2\sigma_A^2(4\alpha-2) + 2\rho(1-r)^2\sigma_A^2(1-2\alpha)\right] + L_{t-1}^2(1-r)^2\sigma_L^2(4\alpha-2) = 0. \tag{40}$$

The unique solution is $\alpha = 0.5$. The second-order derivative of the expected counterparty's exposure is

$$\begin{aligned}\frac{d^2E}{d\alpha^2} = {} & \frac{1}{2}\frac{d\sigma_t^{-1}}{d\alpha}\frac{d\sigma_t^2}{d\alpha}\varphi(\frac{D-\mu_t}{\sigma_t}) - (-\frac{1}{2}\frac{1}{\sigma_t}\frac{d\frac{d\sigma_t^2}{d\alpha}}{d\alpha}\varphi(\frac{D-\mu_t}{\sigma_t})) \\ & - (-\frac{1}{2}\frac{1}{\sigma_t}\frac{d\sigma_t^2}{d\alpha}(-(\frac{D-\mu_t}{\sigma_t})\varphi(\frac{D-\mu_t}{\sigma_t})\frac{d\frac{D-\mu_t}{\sigma_t}}{d\alpha})),\end{aligned} \tag{41}$$

which is equivalent to

$$\frac{d^2E}{d\alpha^2} = \frac{1}{2}\varphi\left(\frac{D-\mu_t}{\sigma_t}\right)\left(\frac{d(\sigma_t^2)^{-\frac{1}{2}}}{d\alpha} + \frac{1}{\sigma_t}\frac{d\frac{d\sigma_t^2}{d\alpha}}{d\alpha} + \frac{1}{2}\frac{(D-\mu_t)^2}{\sigma_t^5}(\frac{d\sigma_t^2}{d\alpha})^2\right), \tag{42}$$

and comprises to

$$\frac{d^2E}{d\alpha^2} = \frac{1}{2}\varphi\left(\frac{D-\mu_t}{\sigma_t}\right)\left(\left(\frac{d\sigma_t^2}{d\alpha}\right)^2\frac{D-\mu_t-\sigma_t^2}{2\sigma_t^5} + \frac{1}{\sigma_t}\frac{d^2\sigma_t^2}{d\alpha^2}\right), \tag{43}$$

where

$$\frac{d^2\sigma_t^2}{d\alpha^2} = \frac{d}{d\alpha}\left(A_{t-1}^2\left[(1-r)^2\sigma_A^2(4\alpha-2) + 2\rho(1-r)^2\sigma_A^2(1-2\alpha)\right] + L_{t-1}^2(1-r)^2\sigma_L^2(4\alpha-2)\right) \tag{44}$$

$$= 2A_{t-1}^2(2-\rho)(1-r)^2\sigma_A^2 + 4L_{t-1}^2(1-r)^2\sigma_L^2 \tag{45}$$

is always positive. For $\alpha = 0.5$ the term $(\frac{d\sigma_t^2}{d\alpha})^2 = 0$ and it follows that $\frac{d^2E}{d\alpha^2} > 0$. Thus, $\alpha = 0.5$ minimizes the exposure E. $\square$

Proposition 2. *If only the volatility of liabilities between life and non-life business varies but $r = r^L = r^{NL}$, $\mu_L = \mu_L^{NL} = \mu_L^L$, the optimal fraction of life business is given as*

$$\alpha^* = 1 - \frac{A_{t-1}^2\left(1-\rho\right)\sigma_A^2 + L_{t-1}^2{\sigma_L^L}^2}{2A_{t-1}^2\left(1-\rho\right)\sigma_A^2 + L_{t-1}^2\left({\sigma_L^L}^2 + {\sigma_L^{NL}}^2\right)}. \tag{46}$$

It is decreasing in higher levels of volatility of life liabilities $(\sigma_L^L)^2$, and increasing in higher levels of volatility of non-life liabilities $(\sigma_L^{NL})^2$. It is decreasing in higher levels of volatility of asset growth σ_A^2 if $\sigma_L^{NL} > \sigma_L^L$.

Proof. Under the conditions above, the expected equity μ_t is again independent from α and its variance is given by

$$\sigma_t^2 = A_{t-1}^2\left(1-r\right)^2(\alpha^2(\sigma_A^L)^2 + (1-\alpha)^2(\sigma_A^{NL})^2 + 2\rho\alpha(1-\alpha)\sigma_A^L\sigma_A^{NL}\right) \tag{47}$$

$$+ L_{t-1}^2(1-r)^2\left(\alpha^2(\sigma_L^L)^2 + (1-\alpha)^2(\sigma_L^{NL})^2\right)$$

The marginal expected exposure is given as

$$\frac{dE}{d\alpha} = \frac{d\sigma_t}{d\alpha}\varphi\left(\frac{D-\mu_t}{\sigma_t}\right). \tag{48}$$

Since $\frac{d\sigma_t}{d\alpha} = \frac{1}{2}\sigma_t^{-1}\frac{d\sigma_t^2}{d\alpha}$, the first order condition is equivalent to $\frac{d\sigma_t^2}{d\alpha} = 0$, which is equivalent to

$$\begin{aligned} &A_{t-1}^2(1-r)^2(2\alpha((\sigma_A^{NL})^2 + (\sigma_A^L)^2 - 2\rho\sigma_A^L\sigma_A^{NL}) - 2(\sigma_A^{NL})^2 + 2\rho\sigma_A^L\sigma_A^{NL}) \\ &+ L_{t-1}^2(1-r)^2(2\alpha((\sigma_L^L)^2 + (\sigma_L^{NL})^2) - 2(\sigma_L^{NL})^2) = 0. \end{aligned} \tag{49}$$

This leads to the optimal fraction of life business α^* given by

$$\begin{aligned} \alpha^* &= \frac{A_{t-1}^2\sigma_A^{NL}\left(\sigma_A^{NL} - \rho\sigma_A^L\right) + L_{t-1}^2\sigma_L^{NL^2}}{A_{t-1}^2\left(\sigma_A^{NL^2} + \sigma_A^{L^2} - 2\rho\sigma_A^L\sigma_A^{NL}\right) + L_{t-1}^2\left(\sigma_L^{L^2} + \sigma_L^{NL^2}\right)} && (50)\\ &= \frac{A_{t-1}^2\sigma_A^2\left(1-\rho\right) + L_{t-1}^2\sigma_L^{NL^2}}{2A_{t-1}^2\left(1-\rho\right)\sigma_A^2 + L_{t-1}^2\left(\sigma_L^{L^2} + \sigma_L^{NL^2}\right)} && (51)\\ &= 1 - \frac{A_{t-1}^2\left(1-\rho\right)\sigma_A^2 + L_{t-1}^2\sigma_L^{L^2}}{2A_{t-1}^2\left(1-\rho\right)\sigma_A^2 + L_{t-1}^2\left(\sigma_L^{L^2} + \sigma_L^{NL^2}\right)} && (52) \end{aligned}$$

Define $\alpha^* = 1 - \frac{X}{Y}$, where $0 < X < Y$. A marginal increase in the asset's volatility relates to

$$\begin{aligned} \frac{d\alpha^*}{d\sigma_A^2} &= -\frac{X'Y - XY'}{Y^2} && (53)\\ &= -\frac{A_{t-1}^2(1-\rho)Y - X2A_{t-1}^2(1-\rho)}{Y^2} && (54)\\ &= -A_{t-1}^2(1-\rho)\frac{Y-2X}{Y^2}, && (55) \end{aligned}$$

which is negative for $Y > 2X$, such that

$$\begin{aligned} &2A_{t-1}^2\left(1-\rho\right)\sigma_A^2 + L_{t-1}^2\left(\sigma_L^{L^2} + \sigma_L^{NL^2}\right) > 2A_{t-1}^2\left(1-\rho\right)\sigma_A^2 + 2L_{t-1}^2\sigma_L^{L^2} && (56)\\ &\Rightarrow \sigma_L^{NL} > \sigma_L^L. && (57) \end{aligned}$$

A marginal increase in the volatility of life insurance's liabilities relates to

$$\frac{d\alpha^*}{d(\sigma_L^L)^2} = -\frac{X'Y - XY'}{Y^2} = -L_{t-1}^2 \frac{Y - X}{Y^2}, \tag{58}$$

which is negative since $Y - X = A_{t-1}^2 (1-\rho)\, \sigma_A^2 + L_{t-1}^2 \sigma_L^{NL^2} > 0$.

A marginal increase in the volatility of non-life liability growth relates to

$$\frac{d\alpha^*}{d(\sigma_L^{NL})^2} = -\frac{X'Y - XY'}{Y^2} = \frac{XL_{t-1}^2}{Y^2} > 0, \tag{59}$$

which is positive. □

Proposition 3. *Assume that $r^L > r^{NL}$. If the previous year's liability growth rate $R_{L,t-1}$ and the size of liabilities L_{t-1} are large enough (i.e. financial distress), $\alpha^* = 0$ is optimal. If the size of liabilities L_{t-1} is sufficiently small and the asset growth rate satisfies a certain condition $R_{A,t-1} > \max(\mu_A,\, D/A_{t-1})$, counterparty's expected exposure is smaller for $\alpha = 1$ than for $\alpha = 0$.*

Proof. For L_{t-1} and $R_{L,t-1}$ sufficiently large, we have that $\Phi\left(\frac{D-\mu_t}{\sigma_t}\right) \approx 1$ and $\varphi\left(\frac{D-\mu_t}{\sigma_t}\right) \approx 0$, since

$$\lim_{L_{t-1}\to\infty} \frac{D-\mu_t}{\sigma_t} = \frac{\alpha((r^L - r^{NL})R_{L,t-1} + (1-r^L)\mu_L^L - (1-r^{NL})\mu_L^{NL}) + r^{NL}R_{L,t-1} + (1-r^{NL})\mu_L^{NL}}{\sqrt{\alpha^2(1-r^L)^2(\sigma_L^L)^2 + (1-\alpha)^2(1-r^{NL})^2(\sigma_L^{NL})^2}}, \tag{60}$$

which is increasing unrestrictedly in $R_{L,t-1}$.

Therefore, the first term $D - \mu_t$ dominates the exposure in equation 11 if L_{t-1} and $R_{L,t-1}$ are large enough. Since $r^L > r^{NL}$, μ_t is monotonic decreasing in α for sufficiently large L_{t-1} (equation 13). Therefore, $\alpha = 0$ is the optimal fraction of life business which maximizes the insurer's expected equity and hence minimizes the counterparty's exposure towards the insurance company.

For $L_{t-1} = 0$, the limit is expressed by

$$\lim_{L_{t-1}\to 0} \frac{D-\mu_t}{\sigma_t} \tag{61}$$

$$= \frac{D - A_{t-1}\left(\alpha((r^L - r^{NL})R_{A,t-1} + (r^{NL} - r^L)\mu_A) + r^{NL}R_{A,t-1} + (1-r^{NL})\mu_A\right)}{\sqrt{A_{t-1}^2\left(\alpha^2(1-r^L)^2\sigma_A^2 + (1-\alpha)^2(1-r^{NL})^2\sigma_A^2 + 2\rho\alpha(1-\alpha)(1-r^L)(1-r^{NL})\sigma_A^2\right)}},$$

which is decreasing in $R_{A,t-1}$. In case of $\alpha = 0$, the expected exposure for a sufficiently small value of liabilities (i.e. no financial distress) converges to

$$\lim_{L_{t-1}\to 0} E(0) = \left(D - A_{t-1}\left(r^{NL}R_{A,t-1} + (1-r^{NL})\mu_A\right)\right)\Phi\left(\frac{D - A_{t-1}\left(r^{NL}R_{A,t-1} + (1-r^{NL})\mu_A\right)}{A_{t-1}(1-r^{NL})\sigma_A}\right) \tag{62}$$

$$+ A_{t-1}(1-r^{NL})\sigma_A\varphi\left(\frac{D - A_{t-1}\left(r^{NL}R_{A,t-1} + (1-r^{NL})\mu_A\right)}{A_{t-1}(1-r^{NL})\sigma_A}\right).$$

In case of $\alpha = 1$, it converges to

$$\lim_{L_{t-1}\to 0} E(1) = \left(D - A_{t-1}\left(r^{L}R_{A,t-1} + (1-r^{L})\mu_A\right)\right)\Phi\left(\frac{D - A_{t-1}(r^{L}R_{A,t-1} + (1-r^{L})\mu_A)}{A_{t-1}(1-r^{L})\sigma_A}\right) \tag{63}$$
$$+ A_{t-1}(1-r^{L})\sigma_A\varphi\left(\frac{D - A_{t-1}(r^{L}R_{A,t-1} + (1-r^{L})\mu_A)}{A_{t-1}(1-r^{L})\sigma_A}\right).$$

The fraction $\alpha = 1$ is preferred over $\alpha = 0$ if

$$\lim_{L_{t-1}\to 0} E(1) < \lim_{L_{t-1}\to 0} E(0). \tag{64}$$

We have that $A_{t-1}(1-r^{L})\sigma_A < A_{t-1}(1-r^{NL})\sigma_A$, so the conditions 65 and 67 must hold

$$D - A_{t-1}\left(r^{L}R_{A,t-1} + (1-r^{L})\mu_A\right) < D - A_{t-1}\left(r^{NL}R_{A,t-1} + (1-r^{NL})\mu_A\right) \tag{65}$$

(66)

and

$$\frac{D - A_{t-1}(r^{L}R_{A,t-1} + (1-r^{L})\mu_A)}{A_{t-1}(1-r^{L})\sigma_A} < \frac{D - A_{t-1}\left(r^{NL}R_{A,t-1} + (1-r^{NL})\mu_A\right)}{A_{t-1}(1-r^{NL})\sigma_A}. \tag{67}$$

(68)

This is the case for $R_{A,t-1} > \mu_A$ and $R_{A,t-1} > D/A_{t-1}$, respectively. Thus, if $R_{A,t-1} > \max\left(\mu_A,\ D/A_{t-1}\right)$ and L_{t-1} is sufficiently small, $E(1)$ is smaller than $E(0)$. Hence, the insurance company minimizes the counterparty's exposure by undertaking a maximum of life insurance business. □

B Empirical Analysis

B.1 System's Index

As in Kubitza and Gründl (2017), we compute the index of a system of institutions 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 a system $\mathbb{S}$ of institutions is given as

$$INDEX_t^{\mathbb{S}|j} = INDEX_{t-1}^{\mathbb{S}|j} \sum_{s \in \mathbb{S} \setminus \{j\}} \frac{MC_{s,t-1}}{\sum_{i \in \mathbb{S} \setminus \{j\}} MC_{i,t-1}} \frac{TR_{s,t}}{TR_{s,t-1}}. \tag{69}$$

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

B.2 Data

B.3 Regressions

	Name	Name
1	AEGON	MARKEL
2	AFLAC	MENORA MIV HOLDING
3	ALLEGHANY	METLIFE
4	ALLIANZ	MGIC INVESTMENT
5	ALLSTATE	MIGDAL INSURANCE
6	AMERICAN FINL.GP.OHIO	MMI HOLDINGS
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	DELTA LLOYD GROUP	SWISS LIFE HOLDING
21	DISCOVERY	SWISS RE
22	EULER HERMES GROUP	TOPDANMARK
23	FAIRFAX FINL.HDG.	TORCHMARK
24	FBD HOLDINGS	TRAVELERS COS.
25	GREAT WEST LIFECO	TRYG
26	GRUPO CATALANA OCCIDENTE	UNIPOL GRUPPO FINANZIARI
27	HANNOVER RUCK.	UNIPOLSAI
28	HANOVER INSURANCE GROUP	UNIQA INSU GR AG
29	HAREL IN.INVS.& FNSR.	UNUM GROUP
30	HELVETIA HOLDING N	VAUDOISE 'B'
31	INTACT FINANCIAL	VIENNA INSURANCE GROUP A
32	LIBERTY HOLDINGS	VITTORIA ASSICURAZIONI
33	LINCOLN NATIONAL	W R BERKLEY
34	LOEWS	WHITE MOUNTAINS IN.GP.
35	MANULIFE FINANCIAL	WUESTENROT & WUERTT.
36	MAPFRE	ZURICH INSURANCE GROUP

Table 12: 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 *Thomon Reuters Worldscope*, *SNL Financial* 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 13: List of all insurance companies included in regressions with reinsurance business as independent variable.

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

	Name	Name
1	AEGON	
2	AFLAC	
3	ALLIANZ	
4	ALLSTATE	
5	AMERICAN INTL.GP.	
6	ASSURED GUARANTY	
7	AXA	
8	GREAT WEST LIFECO	
9	LINCOLN NATIONAL	
10	PHOENIX INSURANCE 1	
11	PRINCIPAL FINL.GP.	
12	SCOR SE	
13	TRAVELERS COS.	
14	UNUM GROUP	
15	W R BERKLEY	

Table 14: List of all insurance companies included in regressions with the proportion of long-term bond investments as independent variable.

The sample is constructed by matching firm-level data from *AM Best*, *Thomon Reuters Worldscope*, *SNL Financial*, *ORBIS Insurance Focus* and *AM Best* 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 market distress within 100 days after the institution's distress event.	Datastream, own calc.
Dependence-consistent ΔCoVaR$^{\leq}$	Difference between VaR of the market conditional on institution being in distress and the VaR of the market conditional on the institution's benchmark state.	Datastream, own calc.
MES	Expected return of an institution when market faces distress.	Datastream, own calc.
Independent variables		
Life premiums	Ratio of gross life premiums to total gross premiums.	ORBIS
Reinsurance assumed	Ratio of reinsurance premiums assumed to total gross premiums.	ORBIS
Total assets	Natural logarithm of total assets in thousands.	Worldscope (WC02999)
MarketCap	Market capitalization in millions.	Worldscope (WC 8001)
Book leverage	Ratio of total assets to book value of equity.	Worldscope (WC02999, WC03501)
Market-to-Book	Ratio of market value equity to book value equity.	Worldscope (WC07210, WC03501)
RoE	Return on Equity per share.	Worldscope (WC08372)
Long-term Bonds	Fraction of long-term bond investments with a maturity of at least 20 years on total investments.	A.M. Best Company

Table 15: List of variables used in the regression model.

The table lists the definitions and data sources of all variables implemented in the regression model. Data is retrieved from *Thomson Reuters Financial Datastream*, *Thomson Worldscope SNL Financial* and *ORBIS Insurance Focus*.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Life^2)	-2.423^{*}	0.035	1.757	0.663
	(1.287)	(0.316)	(1.226)	(1.263)
Premiums.Life	2.592^{**}	-0.041	-1.626	-0.779
	(1.288)	(0.328)	(1.063)	(1.150)
Long.Term.Bonds	-0.0004	-0.001	-0.009^{***}	-0.011^{***}
	(0.001)	(0.001)	(0.003)	(0.003)
Log.Total.Assets	0.009	0.023	0.153^{***}	0.127^{**}
	(0.030)	(0.015)	(0.046)	(0.053)
Market.to.Book	0.048	0.005	-0.322^{**}	-0.307^{**}
	(0.049)	(0.022)	(0.142)	(0.129)
RoE	-0.324	-0.013	-0.009	0.363
	(0.546)	(0.195)	(0.454)	(0.415)
Leverage	-0.003	-0.003	-0.012	-0.011
	(0.003)	(0.003)	(0.009)	(0.010)
I(Premiums.Life^2):Long.Term.Bonds	0.048^{**}	0.003	-0.005	0.010
	(0.022)	(0.005)	(0.018)	(0.020)
Premiums.Life:Long.Term.Bonds	-0.052^{**}	-0.003	0.009	-0.003
	(0.022)	(0.006)	(0.017)	(0.019)
Constant	0.450	0.089	-1.242	-0.423
	(0.564)	(0.254)	(0.931)	(0.995)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	-73.4	-284.4	16.6	-0.2
Observations	118	118	118	118
R^2	0.765	0.900	0.727	0.681
Adjusted R^2	0.725	0.882	0.681	0.626
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 16: OLS Regression (24) for insurance and long-term bond investments: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities and long-term bond investments. All spillover measures are standardized. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Life^2)	−1.829	0.260	2.803**	2.253
	(1.296)	(0.488)	(1.368)	(1.424)
Premiums.Life	1.971	−0.206	−2.452**	−2.005
	(1.301)	(0.493)	(1.190)	(1.274)
Long.Term.Bonds	−0.001	−0.002	−0.006**	−0.007**
	(0.001)	(0.001)	(0.003)	(0.003)
Log.Total.Assets	0.019	0.093***	0.131***	0.115**
	(0.027)	(0.028)	(0.047)	(0.053)
Market.to.Book	0.076*	0.012	−0.310*	−0.295*
	(0.046)	(0.033)	(0.160)	(0.166)
RoE	−0.429	0.103	0.284	0.556
	(0.500)	(0.198)	(0.477)	(0.469)
Leverage	−0.002	−0.016***	−0.016**	−0.020*
	(0.003)	(0.004)	(0.008)	(0.010)
I(Premiums.Life^2):Long.Term.Bonds	0.042*	0.009	−0.007	0.001
	(0.022)	(0.008)	(0.021)	(0.022)
Premiums.Life:Long.Term.Bonds	−0.046**	−0.009	0.008	0.001
	(0.022)	(0.009)	(0.020)	(0.020)
Constant	0.232	−1.080**	−1.049	−0.545
	(0.514)	(0.463)	(1.008)	(1.075)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	−95.4	−226.4	32.7	33.7
Observations	118	118	118	118
R^2	0.789	0.915	0.704	0.632
Adjusted R^2	0.753	0.901	0.654	0.569
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 17: OLS Regression (24) for insurance and long-term bond investments: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities and long-term bond investments. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Life^2)	0.662**	0.288*	1.299***	1.277***
	(0.260)	(0.164)	(0.404)	(0.374)
Premiums.Life	−0.827***	−0.308*	−1.008***	−1.019***
	(0.281)	(0.171)	(0.373)	(0.357)
Leverage	−0.008	−0.005	0.007	0.007
	(0.008)	(0.004)	(0.012)	(0.011)
Log.Total.Assets	0.020	0.031***	0.067**	0.089***
	(0.018)	(0.010)	(0.029)	(0.028)
Market.to.Book	−0.039	−0.045*	−0.163**	−0.172***
	(0.032)	(0.024)	(0.070)	(0.066)
RoE	−0.180	−0.050	−1.308***	−0.996**
	(0.298)	(0.076)	(0.500)	(0.473)
Premiums.Life:Leverage	0.011	0.002	−0.010	−0.011
	(0.009)	(0.006)	(0.017)	(0.015)
Constant	0.412	0.023	−0.298	−0.413
	(0.291)	(0.155)	(0.480)	(0.451)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	51.7	−552.4	440.2	374.8
Observations	517	517	517	517
R^2	0.568	0.625	0.423	0.382
Adjusted R^2	0.555	0.614	0.406	0.363
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 18: OLS Regression (26) for Insurance Business and Leverage: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3) and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Life^2)	0.868***	0.769***	2.253***	2.231***
	(0.265)	(0.236)	(0.406)	(0.391)
Premiums.Life	−0.981***	−0.758***	−1.863***	−1.874***
	(0.282)	(0.254)	(0.374)	(0.380)
Leverage	−0.006	−0.006	0.009	0.004
	(0.008)	(0.006)	(0.011)	(0.011)
Log.Total.Assets	0.027	0.074***	0.065*	0.088**
	(0.018)	(0.015)	(0.038)	(0.036)
Market.to.Book	−0.055	−0.076**	−0.192**	−0.207**
	(0.034)	(0.038)	(0.092)	(0.087)
RoE	−0.101	−0.078	−1.459**	−1.003*
	(0.288)	(0.150)	(0.623)	(0.549)
Premiums.Life:Leverage	0.007	−0.005	−0.019	−0.020
	(0.009)	(0.010)	(0.019)	(0.019)
Constant	0.270	−0.658***	−0.216	−0.397
	(0.298)	(0.231)	(0.653)	(0.624)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	38.3	−110.8	585.8	547.7
Observations	516	516	516	516
R^2	0.558	0.561	0.437	0.395
Adjusted R^2	0.545	0.548	0.421	0.377
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 19: OLS Regression (26) for Insurance Business and Leverage: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3) and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Reinsurance.assumedˆ2)	0.053	0.007	0.941*	0.814
	(0.412)	(0.179)	(0.510)	(0.506)
Reinsurance.assumed	−0.039	0.010	−1.070**	−0.892*
	(0.400)	(0.163)	(0.513)	(0.502)
Log.Total.Assets	0.049*	0.031***	0.102***	0.117***
	(0.025)	(0.010)	(0.039)	(0.037)
Market.to.Book	−0.016	−0.017	−0.157	−0.143
	(0.059)	(0.022)	(0.135)	(0.125)
RoE	−0.440*	−0.069	−1.401***	−1.164***
	(0.261)	(0.058)	(0.429)	(0.399)
Leverage	−0.014*	−0.003	−0.005	−0.006
	(0.007)	(0.003)	(0.011)	(0.010)
Constant	−0.141	−0.066	−0.779	−0.801
	(0.432)	(0.156)	(0.599)	(0.570)
Year Fixed Effects	*Y*	*Y*	*Y*	
Akaike Inf. Crit	100	−411.5	335.2	
Observations	324	324	324	324
R^2	0.483	0.617	0.326	0.268
Adjusted R^2	0.460	0.600	0.296	0.234
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 20: OLS Regression (28) for Reinsurance Business: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3) and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Reinsurance.assumedˆ2)	0.082	−0.290	0.521	0.386
	(0.441)	(0.338)	(0.650)	(0.640)
Reinsurance.assumed	−0.065	0.317	−0.683	−0.514
	(0.409)	(0.305)	(0.639)	(0.626)
Log.Total.Assets	0.058**	0.074***	0.091*	0.102**
	(0.026)	(0.016)	(0.048)	(0.047)
Market.to.Book	−0.044	−0.084*	−0.217	−0.209
	(0.065)	(0.049)	(0.176)	(0.163)
RoE	−0.398	−0.272**	−1.783***	−1.383***
	(0.250)	(0.116)	(0.516)	(0.424)
Leverage	−0.015**	−0.011**	−0.011	−0.013
	(0.007)	(0.005)	(0.013)	(0.012)
Constant	−0.296	−0.701***	−0.472	−0.546
	(0.462)	(0.263)	(0.791)	(0.775)
Year Fixed Effects	*Y*	*Y*	*Y*	
Akaike Inf. Crit	96.7	−93	481.3	
Observations	324	324	324	324
R^2	0.464	0.548	0.259	0.203
Adjusted R^2	0.439	0.527	0.226	0.167
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: OLS Regression (28) for Reinsurance Business: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3) and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$\exp\left(-\Delta\text{CoVaR}^{\leq}\right)$	exp(MES)	exp(beta)
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	0.931^{***}	0.012^{***}	0.042^{***}	1.427^{***}
	(0.121)	(0.002)	(0.006)	(0.200)
Premiums.Life	-1.012^{***}	-0.012^{***}	-0.034^{***}	-1.237^{***}
	(0.134)	(0.003)	(0.007)	(0.222)
Log.Total.Assets	0.009	0.001^{***}	0.002^{***}	0.067^{***}
	(0.010)	(0.0002)	(0.001)	(0.017)
Market.to.Book	-0.041^{**}	-0.002^{***}	-0.006^{***}	-0.121^{***}
	(0.020)	(0.0004)	(0.001)	(0.032)
RoE	-0.180^{*}	-0.002	-0.048^{***}	-1.542^{***}
	(0.105)	(0.003)	(0.006)	(0.209)
Leverage	0.002	-0.0001^{**}	0.00001	0.003
	(0.002)	(0.0001)	(0.0001)	(0.004)
Constant	-0.578^{***}	0.963^{***}	0.957^{***}	-0.099
	(0.187)	(0.004)	(0.009)	(0.295)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	42.3	−3930.8	−3014.5	628.9
Observations	517	517	517	517
Akaike Inf. Crit.	42.280	-3,930.843	-3,014.472	628.870
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 22: Robustness GLM Regression with normally distributed errors for Insurance Business: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities. All spillover measures are standardized. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$\exp\left(-\Delta \text{CoVaR}^{\leq}\right)$	exp(MES)	exp(beta)
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	1.070***	0.028***	0.073***	1.972***
	(0.120)	(0.004)	(0.007)	(0.233)
Premiums.Life	−1.125***	−0.029***	−0.065***	−1.665***
	(0.133)	(0.004)	(0.008)	(0.260)
Log.Total.Assets	0.019*	0.003***	0.002***	0.046**
	(0.010)	(0.0003)	(0.001)	(0.020)
Market.to.Book	−0.061***	−0.003***	−0.007***	−0.117***
	(0.020)	(0.001)	(0.001)	(0.038)
RoE	−0.114	−0.004	−0.056***	−1.543***
	(0.108)	(0.004)	(0.007)	(0.244)
Leverage	0.001	−0.0004***	−0.0002	−0.008*
	(0.002)	(0.0001)	(0.0001)	(0.005)
Constant	−0.764***	0.935***	0.961***	0.195
	(0.186)	(0.006)	(0.010)	(0.344)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	29	−3440.6	−2826.4	787.8
Observations	516	516	516	516
Akaike Inf. Crit.	29.025	-3,440.627	-2,826.377	787.828
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 23: Robustness GLM Regression with normally distributed errors for Insurance Business: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta \text{CoVaR}^{\leq}$ (2), MES (3), and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	0.242	−0.083	−0.132	0.023
	(0.447)	(0.294)	(0.612)	(0.563)
Premiums.Life	−0.404	0.067	0.437	0.248
	(0.464)	(0.301)	(0.566)	(0.552)
Leverage	−0.002	0.001	0.028**	0.025**
	(0.008)	(0.005)	(0.011)	(0.011)
Log.Total.Assets	0.017	0.029***	0.058*	0.081***
	(0.019)	(0.010)	(0.030)	(0.029)
Market.to.Book	−0.035	−0.041*	−0.147**	−0.158**
	(0.031)	(0.023)	(0.065)	(0.062)
RoE	−0.185	−0.054	−1.325***	−1.011**
	(0.281)	(0.072)	(0.438)	(0.420)
I(Premiums.Lifeˆ2):Leverage	0.038	0.033*	0.129***	0.113***
	(0.030)	(0.020)	(0.043)	(0.043)
Premiums.Life:Leverage	−0.030	−0.034	−0.149***	−0.133***
	(0.032)	(0.022)	(0.045)	(0.046)
Constant	0.413	0.024	−0.293	−0.409
	(0.303)	(0.158)	(0.492)	(0.464)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	49.4	−561.5	417.8	355.6
Observations	517	517	517	517
R^2	0.572	0.633	0.450	0.406
Adjusted R^2	0.558	0.621	0.432	0.387
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 24: OLS Regression (31) for Insurance Business and Leverage: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3) and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	0.486	0.618	1.449**	1.613**
	(0.455)	(0.416)	(0.713)	(0.676)
Premiums.Life	−0.595	−0.605	−1.049*	−1.249**
	(0.464)	(0.415)	(0.628)	(0.626)
Leverage	−0.0005	−0.004	0.020	0.013
	(0.008)	(0.008)	(0.015)	(0.015)
Log.Total.Assets	0.025	0.073***	0.060	0.084**
	(0.019)	(0.015)	(0.038)	(0.037)
Market.to.Book	−0.051	−0.075**	−0.183**	−0.201**
	(0.033)	(0.037)	(0.090)	(0.086)
RoE	−0.106	−0.080	−1.469**	−1.010*
	(0.273)	(0.147)	(0.589)	(0.524)
I(Premiums.Lifeˆ2):Leverage	0.034	0.014	0.072	0.056
	(0.029)	(0.026)	(0.051)	(0.053)
Premiums.Life:Leverage	−0.030	−0.020	−0.098*	−0.081
	(0.030)	(0.029)	(0.053)	(0.056)
Constant	0.271	−0.657***	−0.212	−0.394
	(0.307)	(0.234)	(0.657)	(0.629)
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	36.6	−109.5	582.1	546
Observations	516	516	516	516
R^2	0.561	0.561	0.444	0.399
Adjusted R^2	0.547	0.547	0.426	0.380
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 25: OLS Regression (31) for Insurance Business and Leverage: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), MES (3) and beta (4) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Lifeˆ2)	0.699*	0.173	1.492**	1.402**
	(0.418)	(0.185)	(0.626)	(0.591)
Premiums.Life	−0.611	−0.124	−0.877	−0.916
	(0.496)	(0.241)	(0.715)	(0.669)
Reinsurance.assumed	0.100	0.021	−0.453*	−0.373
	(0.144)	(0.059)	(0.272)	(0.261)
I(Premiums.Lifeˆ2):Reinsurance.assumed	−0.060	−0.113	−2.285**	−2.165**
	(0.679)	(0.229)	(1.040)	(0.975)
Premiums.Life:Reinsurance.assumed	−0.071	0.074	2.046*	1.963*
	(0.768)	(0.267)	(1.233)	(1.167)
Constant	0.005	0.0003	0.117	−0.035
	(0.443)	(0.170)	(0.798)	(0.711)
Insurer Controls	*Y*	*Y*	*Y*	*Y*
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	82.2	−414.2	251.4	226.5
Observations	324	324	324	324
R^2	0.520	0.627	0.489	0.416
Adjusted R^2	0.493	0.606	0.461	0.384
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 26: OLS Regression (34) for Insurance and Reinsurance Business: Global Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), and MES (3) on insurance activities. All spillover measures are standardized. Insurer-clustered standard errors are provided in parentheses.

	Dependent variable:			
	$\bar{\psi}$	$-\Delta\text{CoVaR}^{\leq}$	MES	beta
	(1)	(2)	(3)	(4)
I(Premiums.Life^2)	0.893**	0.529	2.607***	2.614***
	(0.401)	(0.322)	(0.800)	(0.802)
Premiums.Life	−0.816*	−0.495	−2.099**	−2.221***
	(0.489)	(0.389)	(0.891)	(0.860)
Reinsurance.assumed	0.063	0.195	−0.446	−0.382
	(0.131)	(0.140)	(0.321)	(0.301)
I(Premiums.Life^2):Reinsurance.assumed	−0.055	0.111	−2.401*	−2.241*
	(0.708)	(0.616)	(1.269)	(1.187)
Premiums.Life:Reinsurance.assumed	0.021	−0.304	2.270	2.163
	(0.783)	(0.682)	(1.465)	(1.360)
Constant	−0.135	−0.652**	0.436	0.252
	(0.448)	(0.291)	(0.994)	(0.907)
Insurer Controls	*Y*	*Y*	*Y*	*Y*
Year Fixed Effects	*Y*	*Y*	*Y*	*Y*
Akaike Inf. Crit	64.5	−110.3	374.6	332.9
Observations	324	324	324	324
R^2	0.523	0.579	0.477	0.443
Adjusted R^2	0.497	0.556	0.448	0.412
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 27: OLS Regression (34) for Insurance and Reinsurance Business: American Non-Financial Sector.

The table presents the estimated coefficients, standard errors, and significance of panel regressions of the Average Excess CoSP (1), dependence-consistent $\Delta\text{CoVaR}^{\leq}$ (2), and MES (3) on insurance activities. The spillover measures are scaled. Insurer-clustered standard errors are provided in parentheses.

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