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Systemic Risk of Insurers Around the Globe

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ABSTRACT

We study the exposure and contribution of 253 international life and non-life insurers to systemic risk between 2000 and 2012. For our full sample period, we find systemic risk in the international insurance sector to be small. In contrast, the contribution of insurers to the fragility of the financial system peaked during the recent financial crisis. In our panel regressions, we find the interconnectedness of large insurers with the insurance sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be primarily driven by the insurers' leverage.

Keywords: Systemic risk, insurer size, interconnectedness, insurance.
JEL Classification: G01, G22.

"SIFIs are financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity."
Financial Stability Board, 11/04/2011

1 Introduction

At the climax of the financial crisis of 2007-2009, American International Group (AIG) became the first example of an insurance company that required (and received) a bailout due to it being regarded as systemically important. Not only did AIG's near-collapse come to the surprise of most economists who considered systemic risk to be confined to the banking sector, but it also spurred a realignment of insurance regulation towards a macroprudential supervision of so-called global systemically important insurers (G-SIIs). As a consequence, the Financial Stability Board (FSB) together with the International Association of Insurance Supervisors (IAIS) recently published a list of nine G-SIIs which will ultimately face higher capital and loss absorbency requirements. In their methodology, insurers are deemed to be of systemic relevance to the global financial sector, if they are of such size and global interconnectedness that their default would cause severe disruptions in the financial sector and subsequently the real economy.

However, the (heavily criticized)[1] methodology proposed by the IAIS has only undergone limited empirical scrutiny so far. Most importantly, the relation between the interconnectedness and systemic risk of insurers has not been analyzed before. In this paper, we intend to fill this gap in the literature by investigating whether the interconnectedness of insurers with the global financial sector in addition to their size increased the insurers' individual contribution to systemic risk. As the main result of our analysis of a panel of global insurers from 2000 to 2012, we find that interconnectedness only increases the systemic vulnerability of large life and non-life insurers. In contrast, the impact of an insurer's interconnectedness on its contribution to systemic risk is much less clear.

[1] For example, the Secretary General of the Geneva Association, John Fitzpatrick, criticized the IAIS indicators for penalizing risk diversification.

Economists have long neglected the potential of the insurance sector to destabilize the whole financial system. In contrast to banks, insurers are not subject to depositor runs and thus do not face the risk of a sudden liquidity drain,[2] hold more capital (see Harrington, 2009) and are less interconnected horizontally with the rest of the financial sector. However, the case of American International Group (AIG) showed that insurers can become systemically important nonetheless if they engage too heavily in business activities outside the traditional insurance sector. As a consequence, the Financial Stability Board urged the IAIS to identify G-SIIs that could potentially destabilize the global financial sector and to implement new regulation for these insurers. Building on the experiences made during the AIG case, the IAIS (2012) recently published a proposal for a methodology for identifying G-SIIs that cites non-core and non-insurance activities, insurer size and interconnectedness as the major drivers of systemic risk in the insurance industry.

Both the question whether insurers can actually become systemically important and the question whether the IAIS's proposed methodology is suitable for identifying G-SIIs remain relatively unanswered in the literature. Early treatments of the topic of systemic risk in insurance include the works by Acharya et al. (2009), Harrington (2009) and Cummins and Weiss (2014).[3] In the latter, it is hypothesized that non-core activities and high degrees of interconnectedness are the primary causes of insurers' systemic relevance. The interconnectedness of insurers is also empirically analyzed by Billio et al. (2012) who argue that illiquid assets of insurers could create systemic risks in times of financial crisis. In a related study, Baluch et al. (2011) conclude that systemic risks exist in the insurance sector even though they are smaller than in banking. More importantly, systemic risk in insurance appears to have grown partly as a consequence to the increasing interconnectedness of insurers and their activities outside the traditional insurance business. Chen et al. (2014) put a special emphasis on the insurance sector but find in their analysis of credit default swap and intraday stock price data that the insurance sector is exposed but does not contribute to systemic risks in

[2] Although one could possibly think of an "insurer run" on life insurance policies, this possibility appears to be highly unlikely as insurance customers are often protected by guarantees and as cancelling a long-term life insurance policy often implies the realization of severe losses. Consequently, there exists no example of a default of an insurer in the past that caused significant contagion effects (see, e.g., Eling and Pankoke, 2012).

[3] Other analyses of systemic risk in insurance include the works of Eling and Schmeiser (2010); Lehmann and Hofmann (2010) and van Lelyveld et al. (2011).

the banking sector. While the former two studies are only concerned with the interconnectedness of banks and insurers, Weiß and Mühlnickel (2014b) also study the impact of size, leverage and other idiosyncratic characteristics included in the IAIS methodology on the systemic risk exposure and contribution of U.S. insurers during the financial crisis.[4] Most importantly, they find that insurer size seems to have been a major driver of the systemic risk exposure and contribution of U.S. insurers. Several of the IAIS indicators (like, e.g., geographical diversification), however, do not appear to be significantly related to the systemic risk of insurers. Finally, Weiß and Mühlnickel (2014a) support the too-big-to-fail conjecture for insurers by showing that insurer mergers tend to increase the systemic risk of the acquiring insurers.

We complement the existing empirical literature on systemic risk in insurance by performing the first panel regression analysis of the systemic risk exposure and contribution of international insurers. In particular, we test hypotheses that size and interconnectedness could drive the systemic importance of international insurers. To measure an insurer's exposure and contribution to the fragility of the financial sector, we follow Anginer et al. (2014b,a) and Weiß and Mühlnickel (2014a,b) and employ the Marginal Expected Shortfall (MES) of Acharya et al. (2010) and ΔCoVaR methodology of Adrian and Brunnermeier (2014), respectively. We then estimate these measures for a sample of 253 international life and non-life insurers for the period from 2000 to 2012 and perform panel regressions of the quarterly MES and ΔCoVaR estimates. As independent variables, we use insurer-specific and macroeconomic variables that have been discussed in the literature as potential drivers of systemic risk. Most importantly, we employ the measure of interconnectedness proposed by Billio et al. (2012) which is based on a principal component analysis of the stock returns of financial institutions.[5]

Based on a sample of 253 life and non-life insurers, we find systemic risk in the international insurance sector to be small in comparison to previous findings in the literature for banks. However, confirming the results of Baluch et al. (2011), we find a strong upward trend in both the exposure

[4] In a related study, Cummins and Weiss (2013) analyze the characteristics of U.S. insurers that are systemically important based on the insurers' SRISK (see Acharya et al., 2012).

[5] Other potential measures of the interconnectedness of financial institutions include the measures proposed by Billio et al. (2012) and Chen et al. (2014) which are both based on Granger causality tests.

and contribution of insurers to the fragility of the global financial system during the financial crisis. In our panel regressions, we find the interconnectedness of large insurers with the financial sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be primarily driven by the insurers' size and leverage.

The remainder of this article is structured as follows. Section 2 introduces the data and the methodology used in our empirical study. Section 3 presents the results of our investigation into the determinants of systemic risk in the insurance industry. Concluding remarks are given in Section 4.

2 Data

This section describes the construction of our sample and presents the choice of our main independent variables as well as descriptive statistics of our data.

2.1 Sample construction

We construct our data sample by first selecting all publicly listed international insurers from the dead and active firm lists in *Thomson Reuters Financial Datastream*. For reasons of relevance, we concentrate on insurance firms with total assets in excess of $ 1 billion at the end of 2000. We then omit all firms for which stock price data are unavailable in *Datastream*. Next, we exclude all secondary listings and nonprimary issues from our sample. Further, we exclude Berkshire Hathaway which is listed as an insurance company in *Datastream* due to its unusually high stock price. Balance-sheet and income statement data are retrieved from the *Thomson Worldscope* database and all stock market and accounting data are collected in U.S. dollars to minimize a possible bias in our results stemming from currency risk.

Finally, we split our data sample into life and non-life insurers. The definition of life and non-life insurance companies in the company lists of *Datastream* is somewhat fuzzy.[6] Therefore, the

[6] For example, several medical service plans and medical wholesale companies are listed as life insurance companies in *Datastream*'s company lists.

industry classification of *Datastream* is cross-checked with the firms' SIC code (Worldscope data item WC07021, SIC codes 6311, 6321, 6331) and the Industry Classification Benchmark (ICB) code (Worldscope data item WC07040, ICB supersector 8500) to exclude firms which cannot be clearly classified as life or non-life insurance companies.[7] Additionally, all company names are manually screened for words suggesting a non-insurance nature of the companies' business and the respective companies being excluded from the sample. In total, we end up with an international sample of 253 insurers, containing 112 life insurers and 141 non-life insurers. For increased transparency, the names of all insurers in our sample are listed in Appendix A.1.

In the following subsections, we define and discuss the different dependent and independent variables we use in our empirical study. An overview of all variables and data sources is given in Appendix A.2.

2.2 Systemic risk measures

Our analysis focuses on the exposure and contribution of individual insurers to the systemic risk of the global financial sector during the period 2000 through 2012. Consequently, we employ an insurer's Marginal Expected Shortfall (MES), Systemic Risk Index/Capital Shortfall (SRISK) and ΔCoVaR as main dependent variables in our regression analyses. We estimate the three measures of systemic risk for each quarter in our sample using daily stock market data for our sample insurers. Our choice of these systemic risk measures is motivated by the fact that these measures have been extensively discussed in the literature and are also used by regulators and central banks for monitoring financial stability (see Benoit et al., 2013).[8] As our first measure of systemic risk, we use the quarterly Marginal Expected Shortfall which is a static structural form approach to measure an individual insurers' *exposure* to systemic risk. It is defined by Acharya et al. (2010) as

7 Consequently, HMO, managed care and title insurance companies are not included in the final sample.

8 All three systemic risk measures we employ share the property that they are all based on economic theory and capture different aspects of systemic risk. Since the recent financial crisis, several other measures of systemic risk have been proposed in the literature. Further examples for such measures apart from those used in this study are due to De Jonghe (2010); Huang et al. (2012); Schwaab et al. (2011); Hautsch et al. (2014); Hovakimian et al. (2012) and White et al. (2012).

the negative average return on an individual insurers stock on the days a market index experienced its 5% worst outcomes. As a proxy for the market's return, we use the World Datastream Bank Index in our main analysis.

Next, we implement the ΔCoVaR method proposed by Adrian and Brunnermeier (2014), which is based on the tail covariation between the returns of individual financial institutions and the financial system. We use ΔCoVaR as an additional measure of an insurer's *contribution* to systemic risk as Adrian and Brunnermeier (2014) criticize the MES measure for not being able to adequately address the procyclicality that arises from contemporaneous risk measurement.[9] While the unconditional ΔCoVaR estimates are constant over time, the conditional ΔCoVaR is time-varying and estimated using a set of state variables that capture the evolution of tail risk dependence over time. However, since we calculate ΔCoVaR based on stock prices for a given quarter, the standard state variables used for estimating the conditional CoVaR show almost no time-variation. Consequently, we focus on estimating the unconditional version of ΔCoVaR in our analysis. An insurer's contribution to systemic risk is then measured as the difference between CoVaR conditional on the insurer being under distress and the CoVaR in the median state of the institution. A lower value of ΔCoVaR indicates a higher contribution to systemic risk, while a positive MES indicates an exposure to systemic risk rather than a stabilizing effect.

As our third systemic risk measure, we use SRISK which attempts to measure the expected capital shortfall of a firm. SRISK is given as the average quarterly estimate of the Systemic Risk Index as proposed by Acharya et al. (2012) and Brownlees and Engle (2012). An insurer's SRISK is estimated by the insurer's book value of debt weighted with a regulatory capital ratio (set to 8%) plus the weighted long run Marginal Expected Shortfall multiplied by the insurer's market value of equity.

[9] Conversely, Acharya et al. (2010) criticize the ΔCoVaR measure as being based on a non-coherent risk measure.

2.3 Explanatory variables

In this subsection, we characterize the main independent variables we use in our panel regressions and robustness checks later on. In our analysis we attempt to capture the key features that make insurers become systemically relevant. We thus concentrate on the factors that have recently been suggested by the IAIS (2011, 2012) as potential sources of systemic risk in insurance. We therefore include in our regressions proxies for an insurer's size, its capital structure, non-core activities, and interconnectedness with the financial system.

To proxy for the latter, we make use of the measure of interconnectedness of a financial institution proposed by Billio et al. (2012). Let Z_i be the standardized stock returns of the ith institutions and $G = Cov(Z_i, Z_j)_{ij}$ be the covariance matrix of the institutions's daily stock returns. Using principal component analysis, we are able to decompose this matrix into a matrix Λ, which is a diagonal matrix of the eigenvalues $\lambda_1, \ldots, \lambda_N$ of G, and a matrix $L = (L_{ik})_{ik}$ that contains the eigenvectors of the returns' correlation matrix. Billio et al. (2012) then define the system's variance as

$$\sigma_S^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{l=1}^{N} \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k$$

In their work, Billio et al. (2012) argue that the more interconnected a system is, the less eigenvalues are necessary to explain a proportion of H of the system's variance σ_S^2.[10] A univariate measure of an institution's interconnectedness with the system of N financial institutions is then given by

$$PCAS_{i,n} := \sum_{k=1}^{n} \frac{\sigma_i^2}{\sigma_S^2} L_{ik}^2 \lambda_k \bigg|_{h_n > H}$$

where $PCAS_{i,n}$ is the contribution of institution i to the risk of the system, and h_n is $\frac{\sum_{k=1}^{n} \lambda_k}{\sum_{k=1}^{N} \lambda_k}$ with

[10] Following a suggestion in Billio et al. (2012), we set $H = 0.33$.

a prescribed threshold H.[11]

The more interconnected an insurer is with the rest of the financial sector, the higher its systemic relevance will be. We therefore expect our proxy for interconnectedness to enter our regressions of ΔCoVaR with a significant negative sign. Similarly, we expect interconnectedness to have a positive effect on both MES and SRISK, since being more interconnected with the financial system exposes insurers to contagion risks from other banks and insurers.

To proxy for the size of an insurer, we use the natural logarithm of an insurer's total assets.[12] We expect insurer size to be an economically significant driver of systemic risk. On the one hand, a larger company is less likely to suffer from cumulative losses due to its broader range of pooled risks and better risk diversification. On the other hand, an insurer could become more systemically relevant by being too-big-to-fail and too-complex-to-fail (see IAIS, 2012).

Another important explanatory variable in our regressions is an insurer's leverage ratio. We follow Acharya et al. (2010) and Fahlenbrach et al. (2012) and approximate an insurer's leverage as the book value of assets minus book value of equity plus market value of equity, divided by market value of equity. We have no prediction for the sign of the coefficient on leverage in our regression. High leverage is a factor that incentivizes managers into excessive risk-taking to increase a firm's profitability.[13] In contrast, Vallascas and Hagendorff (2011) argue that managers of companies with high leverage could feel pressured by investors to provide enough liquid assets to cover the payment of interests. Consequently, a higher leverage could exert a disciplining function on managers leading to a decrease in an insurer's total risk.

Furthermore, we employ several other insurer- and country-specific characteristics as control variables. We include the variable debt maturity which is defined as the ratio of total long

[11] We calculate the proxy for interconnectedness using data on insurers and banks. To be precise, we employ data on all insurance companies in our sample as well as data on all banks available from *Datastream* with total assets in excess of $ 1 billion at the end of 2000. The total sample used for estimating the interconnectedness of individual insurers comprises 1,491 banks and 253 insurers.

[12] In our robustness checks, we use net revenues, given as the log value of an insurer's total operating revenue, as an alternative proxy for firm size.

[13] Support for this view is found by Acharya et al. (2010), Fahlenbrach et al. (2012) and Hovakimian et al. (2012) who present empirical evidence that banks with low leverage during the crisis performed better and had a smaller contribution to systemic risk.

term debt to total debt. There exists a wide consensus among economists and regulators that the dependence of certain banks and insurers on short-term funding exposed these institutions to liquidity risks during the financial crisis and ultimately led to significant systemic risks (see Brunnermeier and Pedersen, 2009; Cummins and Weiss, 2014; Fahlenbrach et al., 2012). Consequently, the IAIS has included the ratio of the absolute sum of short-term borrowing and total assets in its methodology as a key indicator of systemic relevance. We adopt their line of thought but use total long-term debt instead of short term debt.

To include a proxy for an insurer's investment success in our panel regression, we use the ratio of investment income to net revenues. It is defined as the ratio of an insurer's absolute investment income to the sum of absolute investment income and absolute earned premiums. To characterize the quality of the insurance portfolio, in our analysis we compute the insurer's loss ratio, constructed by adding claim and loss expenses plus long term insurance reserves and dividing by premiums earned. We expect insurers with higher loss ratios to contribute more to systemic risk. In our regressions, we also use an insurer's market-to-book ratio, defined as the market value of common equity divided by the book value of common equity.

Next, we employ the insurers' operating expense ratio, given by the ratio of operating expenses to total assets, to control for the quality of management.[14] Furthermore, we follow the reasoning of the IAIS (2012) and control for the degree to which an insurer engages in non-traditional and non-insurance activities. We use the variable Other income defined as other pre-tax income and expenses besides operating income. If an insurer operates more outside the traditional insurance business, e.g., by mimicking banks or becoming a central counterparty for credit derivatives, the more will it be exposed to systemic risks from the financial sector as its interrelations with other financial institutions increase. Therefore, we expect a positive correlation between other income and systemic risk.

Another variable that captures the non-core activities of insurers is non-policyholder liabilities, which is given by the total on balance-sheet liabilities divided by total insurance reserves. We

[14] In our robustness checks, we also compute the operating expense ratio by dividing operating expenses by earned premiums.

suspect a positive correlation of non-policyholder liabilities and systemic risk as policyholder liabilities are indicative of traditional insurance activities (see IAIS, 2012). To proxy for an insurer's profitability and past performance in our regressions, we use the standard measures Return on Equity (ROE) and Return on Assets (ROA). Higher profits can act as a buffer against future losses thus shielding an insurer against adverse effects spilling over from the financial sector. Additionally, we employ the quarterly buy-and-hold returns on an insurer's stock as an independent variable. It is very likely that insurers that performed well in the past will continue to perform well over time. However, institutions that took on too many risks in the past could also stick to their culture of risk-taking (see Fahlenbrach et al., 2012) and increase their exposure and contribution to systemic risk. We therefore expect this measure to have a positive impact on the systemic risk of insurers.

Finally, we also consider macroeconomic and country-specific variables like the GDP growth rate (in %) and the log of the annual change of the GDP deflator. Moreover, we employ a country's stock market turnover defined as the total value of shares traded in a given country divided by the average market capitalization to proxy for the development of a country's equity market (see, e.g., Levine and Zervos, 1998; Bartram et al., 2012).

2.4 Descriptive statistics

Table I presents descriptive statistics for the dependent and explanatory variables we use in our analysis.

[Place Table I about here]

For our full sample of life and non-life insurers, we only find limited evidence of a systemic importance of insurers. Although weakly economically significant, insurers had mean estimates of MES and ΔCoVaR of only 1% during our full sample period. The summary statistics on SRISK also underline the finding that the majority of insurers did not significantly contribute to the instability of the financial sector. However, the minimum estimate of ΔCoVaR and the maximum SRISK estimate show that at least some insurers contributed significantly to systemic risk at some point during our sample period. Intuitively, we would expect insurers to have experienced the extreme values of systemic relevance during the financial crisis. This intuition is proven in Figure 1 in which we plot the time evolution of the three systemic risk measures we use over the course of our complete sample period.

[Place Figure 1 about here]

We can see from Figure 1 that the mean MES is relatively constant over time, showing a significant peak during the financial crisis. The exposure to systemic risk during this peak, however, is highly economically significant with insurers, on average, suffering losses of 5% on their stocks on those days the market plummeted. Some insurers were hit even harder with MES estimates of up to 10%. The second plot for our estimates of the insurers' ΔCoVaR shows a similar picture. The contribution to systemic risk by insurers was low to non-existent until 2007 when both mean and minimum ΔCoVaR estimates decreased dramatically. After the crisis, the average ΔCoVaR of insurers increased again showing that the average contribution of insurers to systemic risk was again limited. This result is corroborated by the plot of the insurers' SRISK estimates.[15]

Although the summary statistics for our full sample yield some instructive information on our sample, some of our variables differ significantly for life and non-life insurers. To get a better understanding of the composition of our sample, we therefore split our sample into life and non-life insurers and compare selected summary statistics across both lines of business. The resulting summary statistics and tests of the equality of sample means are presented in Table II. Summary statistics are given separately for our full sample period in Panel A and for the sub-sample of the quarters during the financial crisis in Panel B.

[Place Table II about here]

[15] Further summary statistics for our explanatory variables given in Table I show that the average interconnectedness of the insurers in our sample is limited. Some insurers, however, are strongly interconnected with the rest of the global insurance sector. Most notably, AIG, AON, AXA, Genworth, and MunichRe are above the 99% quantile of our interconnectedness variable. The average size of a sample insurer is ca. $ 65 billion. Note that our sample includes both very small (5% quantile: $ 1.2 billion) and very large insurers (95% quantile: $ 331.6 billion).

In Panel A of Table II, we compare the values of the systemic risk measures together with the three main (presumed) determinants of systemic risk (size, leverage, and interconnectedness) for the life and non-life insurers in our sample.

We can see from both Table II that the means of the variables differ substantially for life and non-life insurers. First, both the mean estimates of MES and ΔCoVaR are higher for life insurers than for non-life insurers. In contrast, on average, non-life insurers have significantly higher SRISK estimates than life insurers. These differences are statistically significant although the absolute levels of the average contribution and exposure to systemic risk are again not economically significant (at least not across our full panel).[16]

Concerning the potential drivers of systemic risk in insurance, the univariate analysis given in Table II shows that non-life insurers are, on average, slightly more interconnected but are significantly smaller and less levered than life insurers. Non-life insurers have mean total assets of $ 43 billion while life insurers are significantly larger with mean total assets of $ 94.66 billion. The leverage of the average non-life insurer is 16 whereas the average life insurer has a leverage 56. Although the mean estimates are again distorted in part by the presence of few extreme outliers, the quantiles presented in Table II underline the finding that life insurer are significantly larger and more levered.

Before turning to our panel regression analysis of the systemic relevance of global insurers, we shortly comment on the subset of nine Global Systemically Important Insurers (G-SIIs) as identified by the Financial Stability Board in July 2013. In Table III, we repeat our analysis of the summary statistics of our systemic risk measures and selected explanatory variables for the nine G-SIIs.

[Place Table III about here]

During our full sample period, the nine G-SIIs had average MES and ΔCoVaR estimates that did not significantly differ from those of insurers that were not deemed to be systemically important

16 Furthermore, the differences in the mean SRISK and ΔCoVaR estimates are most likely due to the different sizes of the samples for which both measures can be computed.

by the Financial Stability Board. However, global systemically important insurers had a significantly higher mean SRISK than insurers in our full sample. Most importantly, however, average estimates for the three systemic risk measures of G-SIIs increased significantly during the financial crisis as shown in Figure 2.

[Place Figure 2 about here]

As expected, G-SIIs, on average also had significantly higher total assets and were more interconnected. Interestingly, the mean leverage of the nine G-SIIs was lower than the leverage of both the average life and non-life insurer in our full sample. Not surprisingly, all variables are on average significantly higher during the crisis than in our full sample. Again, however, these univariate results for our full sample period do not take into account the (possibly strong) correlations between size, interconnectedness, and leverage.

3 The determinants of systemic risk of insurers

In this section, we investigate the question which factors determine an insurer's contribution and exposure to systemic risk. First, we comment on the results of our baseline panel regressions. Afterwards, we report and comment the results of various robustness checks.

3.1 Panel Regressions

Based on the findings from our univariate analysis, we now perform a multivariate panel regression analysis of our sample of international insurers. In particular, we intend to test the hypothesis that systemic risk in insurance is predominantly driven by an insurer's size, its leverage, and its interconnectedness with the rest of the insurance sector. In our baseline setting, we perform several panel regressions with the three systemic risk measures introduced in Section 2 as our dependent variables. The set of independent variables includes both the set of key features of systemic relevance as proposed by the IAIS (2012) and various control variables as outlined in Section 2.3 and Table A.2. The econometric strategy we use is illustrated below.

$$
\begin{aligned}
SystemicRisk_{i,t} = \ & \beta_0 \ + \ \beta_1 \cdot Interconnectedness_{i,t-1} + \ \beta_2 \cdot Leverage_{i,t-2} \ + \ \beta_3 \cdot Total\ assets_{i,t-2} \\
& + \ \Omega \cdot Insurer\ controls_{i,t-2} \ + \ \Theta \cdot Country\ controls_{i,t-1} \ + \varepsilon_{i,t}
\end{aligned} \tag{1}
$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables, respectively. To mitigate the possibility of reverse causality between our dependent and explanatory variables driving our results, we lag all explanatory variables based on accounting statements by two quarters. The interconnectedness measure and country controls are lagged by one quarter. Furthermore, we perform separate regressions for life and non-life insurers to account for systematic differences in accounting in different lines of insurance business. In addition, we estimate all panel regressions with clustered standard errors on the country level and with insurer- and time-fixed effects to account for unobserved heterogeneity. The results of our baseline regressions are presented in Table IV.

[Place Table IV about here]

Starting with regressions (1) and (2) of the insurers' ΔCoVaR, we can see that neither the life insurers' interconnectedness nor their size is a significant driver of the contribution to systemic risk. This first finding is in striking contrast to the hypotheses formulated by the IAIS on the pivotal role of size and interconnectedness for an insurer's systemic importance. For the leverage of a firm, we find that leverage enters the regressions with a negative sign. Our results suggest that the more levered a life insurer is, the more it contributes to the system's fragility. This result is statistically significant at the 10%- and 1% level, respectively. Furthermore, the effect is also economically significant. For life insurers, an increase in leverage by one standard deviation leads to a decrease of -13% in ΔCoVaR (1308.26 × -0.0001) whereas for non-life insurers, such an increase is associated with an increase in the contribution to systemic risk by 4% (200.04 × -0.0002). Our result implies that the use of high leverage in the insurance business therefore decreases the value of ΔCoVaR and consequently increases a non-life insurer's contribution to systemic risk.

Next, we report the results of our regressions (3) and (4) of the insurers' Marginal Expected Shortfall as the dependent variable. Interestingly, we find a positive relation between the interconnectedness of a non-life insurer and its exposure to systemic risk spilling over from the insurance sector. We thus conclude that being highly interconnected does not necessarily lead to a significantly higher contribution to systemic fragility, but rather to a higher exposure to adverse spillover effects. Additionally, leverage enters both regressions for life and non-life insurers with a statistically and economically significant positive sign. In our regressions, a one standard deviation increase in the leverage of life insurers is associated with a 26.1% higher MES and therefore an increase of an insurer's exposure to systemic risk (1308.26×0.0002). For comparison, a one standard deviation increase in the leverage of a non-life insurer is associated with an 8% increase in MES (200.04×0.0004). In line with our expectation, higher leverage thus appears to significantly increase an insurer's exposure to systemic risk. Higher operating to total assets ratios are associated with a higher MES of insurers.

Finally, in model specifications (5) and (6), we employ the insurers' SRISK as the dependent variable. Underlining our previous findings from the regressions of ΔCoVaR, we find no evidence for the hypothesis that the contribution of insurers to systemic risk is significantly affected by the interconnectedness of an individual life insurer within financial system. For non-life insurers, we again find leverage to have a mitigating effect on systemic risk with the effect being both statistically and economically significant. However, in contrast to our previous regressions, insurer size is now statistically and economically significantly related to the SRISK of insurers. For the life insurers in our sample, we find an increase of total assets to be associated with an increase in SRISK of approx. 196 million (194.91×1.0075). For non-life insurers, we find the economic significance of size to be even larger with a one standard deviation increase in size being associated with an increase in SRISK by approx. 750 million (134.65×5.5704). These findings for SRISK have to be taken with careful consideration, however, since the adjusted R-squared in the regressions of SRISK is considerably lower than in the regressions of MES and ΔCoVaR.

3.2 Additional analyses

The results of our baseline regressions have produced only weak evidence that size, interconnectedness, and leverage are fundamental drivers of systemic risk in insurance. To get a deeper understanding of the relation between idiosyncratic insurer characteristics and systemic risk, we perform several additional analyses in this subsection.

First, we examine the question whether the exposure and contribution of large insurers to systemic risk are driven by different factors than the systemic risk measures of insurers in our full sample. To this end, we restrict our sample to insurer-quarter observations of institutions in the top 75% quantile of total assets. The motivation behind our analysis is that the relation between some of our explanatory variables and the systemic risk of an insurer might be mitigated or exacerbated by the insurer's size. The results for the regression using insurers in the top total assets quartile only are presented in Table V.

[Place Table V about here]

Several of the results from our baseline regressions carry over to our analysis of large insurers. For example, the inferences for the insurers' leverage remain more or less unchanged. Higher leverage increases both the contribution and the exposure of large life and non-life insurers to systemic risk. While leverage is positively related to the purely equity-based measures of systemic risk, we find a significant negative correlation between leverage and SRISK as our third measure of systemic risk. However, in regression (2) in Table V we find one striking difference. In contrast to our baseline regressions, the interconnectedness of an insurer is now positively related to its contribution to systemic risk. An increased interconnectedness of large insurers induces more contribution to overall systemic risk. This is intuitive, since an interconnected insurance company could possibly contribute to systemic risk, but only if it is relevant or large enough to have devastating effects through a default. Similarly to the analysis of our full sample, insurer size is significant in the regression of the SRISK of non-life insurers. Furthermore, and in line with our expectation, we find higher loss ratios to be positively associated with the contribution of large insurers to systemic risk.

Next, we address the question whether the drivers of systemic risk in insurance differ across countries. In fact, it is very possible that insurance companies and even whole sectors function in a different way than their counterparts in foreign countries. Even more importantly, insurance regulation differs substantially from country to country. Although we control for these systematic differences by the use of country-fixed effects in our robustness checks, it is nevertheless instructive to analyze these country differences in the relation between systemic risk and the insurers' idiosyncratic characteristics in more detail. Our sample is composed of 95 insurers with headquarters located in the United States and 158 insurers from other countries. To analyze the differential drivers of systemic risk, we estimate separate panel regressions for U.S. and non-U.S. insurers. The results are given in Table VI.

[Place Table VI about here]

For U.S. based non-life insurers, interconnectedness enters the regression of ΔCoVaR with a positive coefficient that is statistically significant at the 1% level while for non-U.S. insurers it is significant for both lines of business. On the other hand, interconnectedness seems to slightly increase the values of SRISK for non-life insurers in the U.S. and for life insurers outside the United States. These mixed findings indicate no clear trend on the impact of our interconnectedness measure on the contribution of insurers to systemic risk. With the exception of the regressions of the SRISK estimates of non-life insurers outside the U.S., total assets is not a statistically significant determinant of systemic risk. In contrast, leverage is significantly related to the exposure to systemic risk of non-life insurers (U.S. and non-U.S.) and life insurers (only non-U.S.). Our results suggest that the impact of leverage on the exposure and contribution of systemic risk does not vary across countries or lines of business.

Finally, we investigate the question whether our results change significantly if we restrict our sample to the time period of the financial crisis. In particular, we hypothesize that size, interconnectedness, and leverage might only have been key drivers of systemic risk in insurance during the financial crisis. To this end, in Table VII, we repeat our previous baseline regressions but restrict our sample to a smaller time period covering the period from Q1 2006 to Q4 2010 (i.e., the time around and during the financial crisis).

[Place Table VII about here]

This time, we find no statistically significant impact of interconnectedness on any of the systemic risk measures. Again, insurer size does not appear to be systematically related to systemic risk of insurers except for SRISK of non-life insurers where we, again, find a positive relation. While the signs of the coefficients for leverage remain the same, we only find a statistically significant impact on systemic risk for non-life insurers. The economic significance of this effect is, however, moderate with a one standard deviation increase in leverage causing a change of almost minus one percent in ΔCoVaR during the crisis period ($23.42 \times -0.0003 = -0.7026$). In the cross-section of non-life insurers' MES during the crisis period, a one standard deviation increase in leverage is associated with an 1.4% higher exposure to systemic risk (23.42×0.0006).

3.3 Insurers and the Systemic Risk in the Financial Sector

While we have investigated the factors influencing the marginal systemic risk of insurers at the micro-level, we have not yet addressed the overall level of systemic risk that emanates from the insurance sector (and its possible macroeconomic consequences). In our final analysis, we therefore employ a macro-level measure of systemic risk to capture the insurance sector's propensity to cause real macroeconomic downturns. More, specifically, we employ the CATFIN measure introduced by Allen et al. (2012) and compare their results with the CATFIN measure estimated for our sample of insurers. CATFIN is defined as the average of three Value-at-Risk estimates of monthly stock returns in excess of the 1-month treasury bill rate. We fit the Generalized Pareto Distribution and the Skewed Generalized Error Distribution to generate Value-at-Risk estimates from the cross-section of our insurers' monthly stock returns at the 99% level. Additionally, the third estimate is from the cross-sectional 1% sample quantile. The resulting CATFIN measures are plotted in Figure 3 for the time period 07/2001 to 12/2012.

[Place Figure 3 about here]

From the figure, we can see that the time evolution of the two time series of CATFIN estimates are very similar, but vary in magnitude. Before the crisis, the estimated index values are closely together until the beginning of the crisis. While the insurer CATFIN peaks at around 60% in the beginning of 2009, the original estimates from Allen et al. (2012) reach a maximum of over 70%. The monthly values for the original CATFIN index seem to be higher than the insurer CATFIN for the most part after the crisis. Despite the small difference in the magnitude of the peaks of both CATFIN time series, the plot in Figure 3 underlines the finding that the overall level of systemic risk in the insurance sector was significant and high, especially during the crisis. However, another important insight from Figure 3 is that the overall level of systemic risk in the insurance sector fails to predict economic downturns, since insurer stocks seem to lag behind the overall financial sector.

3.4 Robustness checks

We also estimate regressions in which we employ alternative measures of an insurer's size (net revenues instead of total assets), profitability (ROE instead of ROA) and investment activity (ratio of the insurers investment income to net revenues instead of the ratio of the insurers absolute investment income to the sum of absolute investment income and absolute earned premiums), respectively. Additional regressions using the beta of an insurer's stock yield no change in our results. As mentioned before, we also replace total assets with premiums earned in the calculation of our variable operating expenses. However, our previous conclusions remain valid.

Next, it could be argued that our results are driven by the specific manner in which we estimate the Marginal Expected Shortfall and the other systemic risk measures. To control for this potential bias, we recalculate MES and ΔCoVaR using three alternative indexes. To be precise, we employ the World DS Full Lin Insurer Index, the MSCI World Banks Index and the MSCI World Insurance Index taken from *Datastream*. The results show that our conclusions remain unchanged.

Another potential concern with our analysis could be that some of the insurers in our sample might in fact just be locally rather than internationally active market participants. Consequently, the presence of local insurers in our sample could bias our results on systemic risk as the systemic relevance of locally active insurers should generally lower than for globally important insurers. However, we believe that the inclusion of locally active insurers in the context of our analysis is sensible for the following reasons. First, we cannot rule out the possibility that insurers with insurance activities in only their home country contribute to global systemic risk due to off-balance sheet and non-insurance activities. Second, sheer size and relevance in an insurer's home country might be enough to destabilize a nation's economy and thus cause global financial stability.[17] Nevertheless, we perform an additional robustness check in which we include in our baseline regressions the variable Foreign sales, which is the ratio of an insurer's international sales to its total sales, to control for business activities abroad. Including this factor does neither change our main results, nor is the variable significant in any of the regressions.

Additionally, we employ GMM-sys regressions (see Blundell and Bond, 1998) that include one lag of our dependent variables and explanatory variables lagged by one quarter. In these regressions, double-lagged values of the insurer characteristics are used as instruments for estimation. In doing so, we mitigate concerns on possible endogeneity in our regression models. Our main results, however, remain valid.

Finally, we winsorize all data at the 1% and 99% quantiles to minimize a possible bias due to outliers and reestimate all our regressions using winsorized data. The results of these alternative regressions are qualitatively and quantitatively similar to those reported in the paper.

4 Conclusion

In this paper, we analyze the exposure and contribution of 253 international life and non-life insurers to global systemic risk in the period from 2000 to 2012. As our main result, we find sys-

[17] The anecdotal evidence of the inclusion of the Ping An Insurance Group in the list of the nine G-SIIs underlines this notion.

temic risk in the international insurance sector to be small in comparison to previous findings in the literature for banks in our full sample. During the financial crisis, however, insurers did contribute significantly to the instability of the financial sector. Further, we conclude that systemic risk of insurers is determined by various factors including an insurer's interconnectedness and leverage, the magnitudes and significances of these effects, however, differ depending on the systemic risk measure used and with the analyzed insurer line and geographic region. Most interestingly, we find the interconnectedness of large insurers with the insurance sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be driven by (among others) leverage, loss ratios, and the insurer's funding fragility.

Our results also show that life insurers do not contribute significantly more to global systemic risk than non-life insurers. In addition, there seems to be little difference in the interconnectedness of life and non-life insurers. In our study, we find no convincing evidence in support of the hypothesis that insurer size is a fundamental driver of the contribution of an insurer to systemic risk. In contrast to the banking sector, we show that the insurance sector predominantly suffers from being exposed to systemic risk, rather than adding to the financial system's fragility. Finally, our study reveals that both the systemic risk exposure and the contribution of international insurers were limited prior to the financial crisis with all measures of systemic risk increasing significantly during the crisis. In contrast to the banking sector, however, systemic risk in the insurance sector does not appear to lead but rather follow macroeconomic downturns as evidenced by our analysis of the insurers' CATFIN estimates.

A Appendix

Table A.1: Sample Insurance Companies.

The appendix lists all international insurance companies that are used in the empirical study. The sample is constructed by first selecting all international insurers from the country and dead-firm lists of *Thomson Reuters Financial Datastream*. The list is then corrected for all companies for which stock price and balance sheet data are not available from *Thomson Reuters Financial Datastream* and *Worldscope*. The names of the companies are retrieved from the *Worldscope* database (item WC06001).

ALEA GROUP HOLDINGS	AXA ASIA PACIFIC	ERGO PREVIDENZA
CHAUCER HOLDINGS PLC	AXA LEBENSVERSICH	ERGO-VERSICHERUNG
21ST CENTURY INS	AXA KONZERN AG	ERIE FAMILY LIFE INS
ACE LIMITED	AXA PORTUGAL SEGUROS	ERIE INDEMNITY
AEGON N.V.	AXA VERSICHERUNG AG	ETHNIKI GREEK INS
AFFIN-ACF HOLDINGS	AXIS CAPITAL HLDG	EULER HERMES
AFLAC INCORPORATED	BALOISE HOLDING AG	EVEREST RE GROUP
AFRICAN LIFE	BENFIELD GROUP LTD	FAIRFAX FIN’L HLDGS
AGEAS SA	BRIT INSURANCE HOLD	FBD HOLDINGS PLC
ASSURANCES GENERALES	CAPITAL ALLIANCE	FBL FINANCIAL GROUP
AIOI INSURANCE	CASH.LIFE AG	FINANCIAL INDUSTRIES
ALFA CORPORATION	CATHAY FINANCIAL	FINAXA SA
ALLEANZA ASSICUR.	CATLIN GROUP LTD	FIRST FIRE & MARINE
ALLEGHANY CORP	CATTOLICA ASS	FONDIARIA - SAI SPA
ALLIANZ SE	CESKA POJISTOVNA A.S	FOYER S.A.
ALLIANZ LEBENSVERS.	CHALLENGER FIN’L SVC	FPIC INSURANCE GROUP
ALLSTATE CORPORATION	CHESNARA PLC	FRIENDS PROVIDENT
ALM BRAND AS	CHINA LIFE INSURANCE	FUBON FINANCIAL
ALTERRA CAPITAL	CHINA TAIPING INSU	FUJI FIRE& MARINE INS
AMBAC FINANCIAL	CHUBB CORP (THE)	GENERALI (SCHWEIZ)
AMERICAN NATIONAL	CINCINNATI FINL CORP	GENERALI DEUTSCH
AMERICAN PHYSICIANS	CLAL INSURANCE ENT	GENERALI HOLDING VIE
AMERICAN EQUITY INV	CNA FINANCIAL CORP	GENWORTH FIN’L, INC.
AMERICAN FIN’L GROUP	CNA SURETY CORP	GLOBAL INDEMNITY
AMERICAN INT’L GROUP	CNO FINANCIAL	GRUPO NACIONAL
AMERUS GROUP CO	CNP ASSURANCES	GRUPO PROFUTURO
AMLIN PLC	CODAN A/S	GREAT EASTERN HLDGS
AMP LIMITED	GROUPE COFACE	GREAT WEST LIFECO
ANN & LIFE RE HLDGS	COMMERCE GROUP, INC.	GRUPO CATALANA
AON PLC	MILANO ASSICURAZIONI	GREAT AMERICAN FIN’L
ARAB INSURANCE GROUP	COX INSURANCE	HANNOVER RUECK SE
ARCH CAPITAL GROUP	DAI-ICHI LIFE INSU	HANOVER INSURANCE
ARGONAUT GROUP, INC.	DAIDO LIFE INSURANCE	HAREL INSUR INVEST
ARTHUR J GALLAGHER	DBV WINTERTHUR	HARLEYSVILLE GROUP
ASIA FINANCIAL HLDGS	DELPHI FINANCIAL GRP	HARTFORD FINL SRVC
ASPEN INSURANCE HOLD	DELTA LLOYD LEBENS	HCC INS HOLDINGS
ASSICUR GENERALI SPA	DONGBU INSURANCE CO.	HELVETIA HOLDING
ASSURANT INC	DEUTSCHE AERZTEVERS	HILB, ROGAL & HOBBS
ASSURED GUARANTY LTD	E-L FINANCIAL CORP.	HILLTOP HOL
AVIVA PLC	EMPLOYERS HOLDINGS	HISCOX PLC
AXA SA	ENDURANCE SPECIALTY	HORACE MANN EDUCATRS

Table A.1: Sample Insurance Companies (continued).

HYUNDAI M & F INS.	OLD REPUBLIC INTL	SWISS RE
INDUSTRIAL ALLIANCE	PARTNERRE LTD.	TAIWAN LIFE INSURANC
INFINITY PROP & CAS	PENN TREATY AMERICAN	TAIYO LIFE INSURANCE
ING GROEP N.V.	PERMANENT TSB GROUP	TOKIO MARINE
INSURANCE AUSTRALIA	PHILADELPHIA CORP	TONG YANG LIFE INS
INTACT FINANCIAL	PHOENIX COMPANIES	TOPDANMARK A/S
IPC HOLDINGS, LTD.	PHOENIX HOLDINGS	TORCHMARK CORP
JARDINE LLOYD	PICC PROPERTY	TORO ASSICURAZIONI
JEFFERSON-PILOT CORP	PING AN INSURANCE	TOWER LTD
JOHN HANCOCK FIN SVC	PLAT UNDERWRITERS	TRANSATLANTIC HLDGS
KANSAS CITY LIFE INS	PMA CAPITAL CORP	TRAVELERS COS
KEMPER	POHJOLA-YHTYMA OYJ	TRAVELERS PROPERTY
KINGSWAY FINANCIAL	POWER CORP OF CANADA	TRYG A/S
KOELNISCHE RUECKVER.	POWER FINANCIAL CORP	UICI
KOREAN REINSURANCE	PREMAFIN FINANZIARIA	UNIPOL GRUPPO FIN
LANDAMERICA FINL GRP	PRESIDENTIAL LIFE	UNIQA INSUR
LEGAL & GEN’L GRP	PRINCIPAL FINL GROUP	UNITED FIRE
LIBERTY GROUP LTD	PROASSURANCE CORP	PROVIDENT COMPANIES
LIBERTY HOLDINGS	PROGRESSIVE CORP	WAADT VERSICHERUNGEN
LIG INSURANCE CO LTD	PROMINA GROUP	VESTA INSURANCE GRP
LINCOLN NAT’L CORP	PROTECTIVE LIFE CORP	VIENNA INSURANCE
LOEWS CORPORATION	PRUCO LIFE INSURANCE	VITTORIA ASSICURAZIO
MAA GROUP	PRUDENTIAL PLC	W R BERKLEY CORP.
MANULIFE FINANCIAL	PRUDENTIAL FINANCIAL	WELLINGTON
MAPFRE SA	QBE INSURANCE GROUP	WESCO FINANCIAL CORP
MARKEL CORP	RIUNIONE ADRIATICA	WHITE MOUNTAIN INSUR
MARSH & MCLENNAN CO.	REINSURANCE GROUP	WILLIS GROUP
MBIA INC	RENAISSANCERE HLDGS	WUERTTEMBERGISCHE LE
MEDIOLANUM	RHEINLAND HOLDING	XL GROUP PLC
MENORAH MIVTACHIM	RLI CORP	ZENITH NATIONAL
MERCURY GENERAL CORP	RSA INSURANCE GROUP	ZURICH INSURANCE
METLIFE INC	SAFECO CORPORATION	
MIDLAND COMPANY	SAFETY INSURANCE GP	
MIGDAL INSURAN & FIN	SAMPO OYJ	
MIIX GROUP, INC	SAMSUNG FIRE & MARINE	
MNI HOLDINGS BHD	SOUTH AFRICAN NAT’L	
MONTPELIER RE HLDGS	SCHWEIZERISCHE NAT	
MONY GROUP INC.	SCOR SE	
MS& AD INSURANCE	SCOTTISH RE GROUP	
MUENCHENER	SELECTIVE INSURANCE	
NATIONAL WESTERN	SHIN KONG FINANCIAL	
NATIONWIDE FIN’L	SKANDIA FORSAKRINGS	
NAVIGATORS GROUP INC	SOMPO JAPAN INSURANC	
NIPPONKOA INS	SAINT JAMES’S PLACE	
NISSAY DOWA GEN	STANCORP FINANCIAL	
NISSHIN FIRE/MAR INS	STATE AUTO FINANCIAL	
NUERNBERGER BET.-AG	STOREBRAND ASA	
ODYSSEY RE	SUL AMERICA SEGUROS	
OHIO CASUALTY CORP	SUN LIFE FINANCIAL	
OLD MUTUAL PLC	SWISS LIFE HOLDING	

Table A.2: Variable definitions and data sources.

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. The insurer characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	*Definition*	*Data source*
Dependent variables		
ΔCoVaR	Unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2014), measured as the difference of the Value-at-risk (VaR) of a financial sector index conditional on the distress of a particular insurer and the VaR of the sector index conditional on the median state of the insurer.	Datastream, own calc.
MES	Quarterly Marginal Expected Shortfall as defined by Acharya et al. (2010) as the average return on an individual insurer's stock on the days the *World Datastream Bank* index experienced its 5% worst outcomes.	Datastream, own calc.
SRISK	Average quarterly estimate of the Systemic Risk Index as proposed by Acharya et al. (2012) and Brownlees and Engle (2012). The SRISK estimate for insurer i at time t is given by $SRISK_{i,t} = k\,(Debt_{i,t}) - (1-k)\,(1 - LRMES_{i,t})\,Equity_{i,t}$ where k is a regulatory capital ratio (set to 8%), $Debt_{i,t}$ is the insurer's book value of debt, $LRMES_{i,t}$ is the long run Marginal Expected Shortfall defined as $1 - \exp(-18 \cdot MES)$, MES is the estimated Marginal Expected Shortfall and $Equity_{i,t}$ is the insurer's market value of equity.	Datastream, Worldscope (WC03351, WC08001), own. calc.
Insurer characteristics		
Beta	Beta of the capital asset pricing model measuring the market sensitivity of a firm and a local market index of the insurer's country.	Worldscope (WC09802).
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251, WC03255).
Foreign sales	International sales divided by net revenues (times 100)	Worldscope (WC08731).
Investment success	Ratio of insurer's investment income to net revenues.	Worldscope (WC01001, WC01006), own calc.
Interconnectedness	PCAS measure as defined in Billio et al. (2012). PCAS is constructed using a decomposition of the variance-covariance matrix of the insurers' daily, standardized stock returns.	Datastream, own calc.
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity.	Worldscope (WC02999, WC03501, WC08001), own calc.
Loss ratio	Ratio of claim and loss expenses plus long term insurance reserves to earned premiums.	Worldscope (WC15549).

Table A.2: Variable definitions and data sources (continued).

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. The insurer characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	*Definition*	*Data source*
Insurer characteristics		
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210, WC03501).
Net revenues	Log value of total operating revenue of the insurer.	Worldscope (WC01001).
Non-Policyholder Liabilities	Total on balance sheet liabilities divided by total insurance reserves.	Worldscope (WC03351, WC03030).
Operating expenses	Ratio of operating expenses to total assets.	Worldscope (WC01249, WC02999).
Other income	Other pre-tax income and expenses besides operating income.	Worldscope (WC01262).
Performance	Quarterly buy-and-hold return on an insurer's stock.	Datastream, own calc.
Return on Assets	Return of the insurer on it's total assets after taxes (in %).	Worldscope (WC08326).
Return on Equity	An insurer's earnings per share during the last 12 months over the prorated book value per share times 100 (in %).	Worldscope (WC08372).
Total assets	Natural logarithm of a insurer's total assets.	Worldscope (WC02999).
Country characteristics		
GDP growth	Annual real GDP growth rate (in %).	WDI database (World Bank).
Inflation	Log of the annual change of the GDP deflator.	WDI database (World Bank)
Stock market turnover	Total value of shares traded in a given country divided by the average market capitalization.	WDI database (World Bank).

References

Acharya, V. V., J. Biggs, M. Richardson, and S. Ryan (2009): "On the Financial Regulation of Insurance Companies," Working paper, New York University.

Acharya, V. V., R. F. Engle, and M. Richardson (2012): "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks," *American Economic Review: Papers and Proceedings*, 102(3), 59–64.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2010): "Measuring Systemic Risk," Working paper, New York University.

Adrian, T. and M. K. Brunnermeier (2014): "CoVaR," *Federal Reserve Bank of New York Staff Reports 348*.

Allen, L., T. G. Bali, and Y. Tang (2012): "Does Systemic Risk in the Financial Sector Predict Future Economic Downturns?" *Review of Financial Studies*, 25(10), 3000–3036.

Anginer, D., A. Demirgüç-Kunt, and M. Zhu (2014a): "How does Bank Competition Affect Systemic Stability?" *Journal of Financial Intermediation*, 23, 1–26.

Anginer, D., A. Demirgüç-Kunt, and M. Zhu (2014b): "How Does Deposit Insurance Affect Bank Risk? Evidence from the Recent Crisis," *Journal of Banking and Finance*, 48, 312–321.

Baluch, F., S. Mutenga, and C. Parsons (2011): "Insurance, Systemic Risk and the Financial Crisis," *The Geneva Papers on Risk and Insurance*, 36, 126–163.

Bartram, S. M., G. W. Brown, and R. M. Stulz (2012): "Why Are U.S. Stocks More Volatile?" *Journal of Finance*, 67(4), 1329–1370.

Benoit, S., G. Colletaz, C. Hurlin, and C. Pérignon (2013): "A Theoretical and Empirical Comparison of Systemic Risk Measures," Working Paper.

Billio, M., A. W. Lo, M. Getmansky, and L. Pelizzon (2012): "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors," *Journal of Financial Economics*, 104, 535–559.

Blundell, R. and S. Bond (1998): "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87, 115–143.

Brownlees, C. T. and R. Engle (2012): "Volatility, Correlation and Tails for Systemic Risk Measurement," Working Paper.

Brunnermeier, M. K. and L. H. Pedersen (2009): "Market Liquidity and Funding Liquidity," *Review of Financial Studies*, 22, 2201–2238.

Chen, H., J. D. Cummins, K. S. Viswanathan, and M. A. Weiss (2014): "Systemic Risk and the Inter-Connectedness between Banks and Insurers: An Econometric Analysis," *Journal of Risk and Insurance*, 81(3), 623–652.

CUMMINS, J. D. AND M. A. WEISS (2013): “Systemic Risk and Regulation of the U.S. Insurance Industry,” Networks Financial Institute Policy Brief 2013-PB-02.

——— (2014): “Systemic Risk and the U.S. Insurance Sector,” *Journal of Risk and Insurance*, 81(3), 489–528.

DE JONGHE, O. (2010): “Back to the Basics in Banking? A Micro-Analysis of Banking System Stability,” *Journal of Financial Intermediation*, 19, 387–417.

ELING, M. AND M. PANKOKE (2012): “Systemic risk in the insurance sector -What do we know?” Working paper, St. Gallen University.

ELING, M. AND H. SCHMEISER (2010): “Insurance and credit crisis: Impact and ten consequences for risk management supervision,” *Geneva Papers on Risk and Insurance - Issues and Practice*, 35, 9–34.

FAHLENBRACH, R., R. PRILMEIER, AND R. M. STULZ (2012): “This Time is the Same: Using Bank Performance in 1998 to Explain Bank Performance During the Recent Financial Crisis,” *Journal of Finance*, 67, 2139–2185.

HARRINGTON, S. E. (2009): “The Financial Crisis, Systemic Risk, and the Future of Insurance Regulation,” *Journal of Risk and Insurance*, 76, 785–819.

HAUTSCH, N., J. SCHAUMBURG, AND M. SCHIENLE (2014): “Financial Network Systemic Risk Contributions,” *Review of Finance*, forthcoming.

HOVAKIMIAN, A., E. KANE, AND L. LAEVEN (2012): “Variation in Systemic Risk at US Banks During 1974-2010,” *NBER Working Paper No. 18043*.

HUANG, X., H. ZHOU, AND H. ZHU (2012): “Systemic Risk Contribution,” *Journal of Financial Services Research*, 42, 55–83.

IAIS (2011): “Insurance and Financial Stability,” Basel.

——— (2012): “Global Systemically Important Insurers: Proposed Assessment Methodology,” Basel.

LEHMANN, A. AND D. HOFMANN (2010): “Lessons learned fron the financial crisis for risk management: Contrasting developments in insurance and banking,” *Geneva Papers on Risk and Insurance - Issues and Practice*, 35, 63–78.

LEVINE, R. AND S. ZERVOS (1998): “Stock markets, banks, and economic growth,” *American Economic Review*, 88(3), 537–558.

SCHWAAB, B., S.-J. KOOPMAN, AND A. LUCAS (2011): “Systemic risk diagnostics, coincident indicators and early warning signals,” Technical report.

VALLASCAS, F. AND J. HAGENDORFF (2011): “The Impact of European Bank Mergers on Bidder Default Risk,” *Journal of Banking and Finance*, 35, 902–915.

van Lelyveld, I., F. Liedorp, and M. Kampman (2011): "An empirical assessment of reinsurance risk," *Journal of Financial Stability*, 7(4), 191–203.

Weiss, G. and J. Mühlnickel (2015): "Consolidation and Systemic Risk in the International Insurance Industry," Working Paper.

——— (2014): "Why Do Some Insurers Become Systemically Relevant?" *Journal of Financial Stability*, 13, 95–117.

White, H., T.-H. Kim, and S. Manganelli (2012): "VAR for VaR: Measuring Tail Dependence Using Multivariate Regression Quantiles," European Central Bank Working Paper.

Figures and Tables

Figure 1: Time evolution of the systemic risk measures in the period from 2000 to 2012.

This figure plots the evolution of the systemic risk measures Marginal Expected Shortfalls (MES), SRISK, and ΔCoVaR over our full sample period from 2000 to 2012. The sample consists of 253 international life and non-life insurers. In each plot, the mean of the respective risk measure (black line) is plotted against the corresponding 10% and 90% percent quantiles (grey lines). All variables and data sources are defined in Appendix A.2.

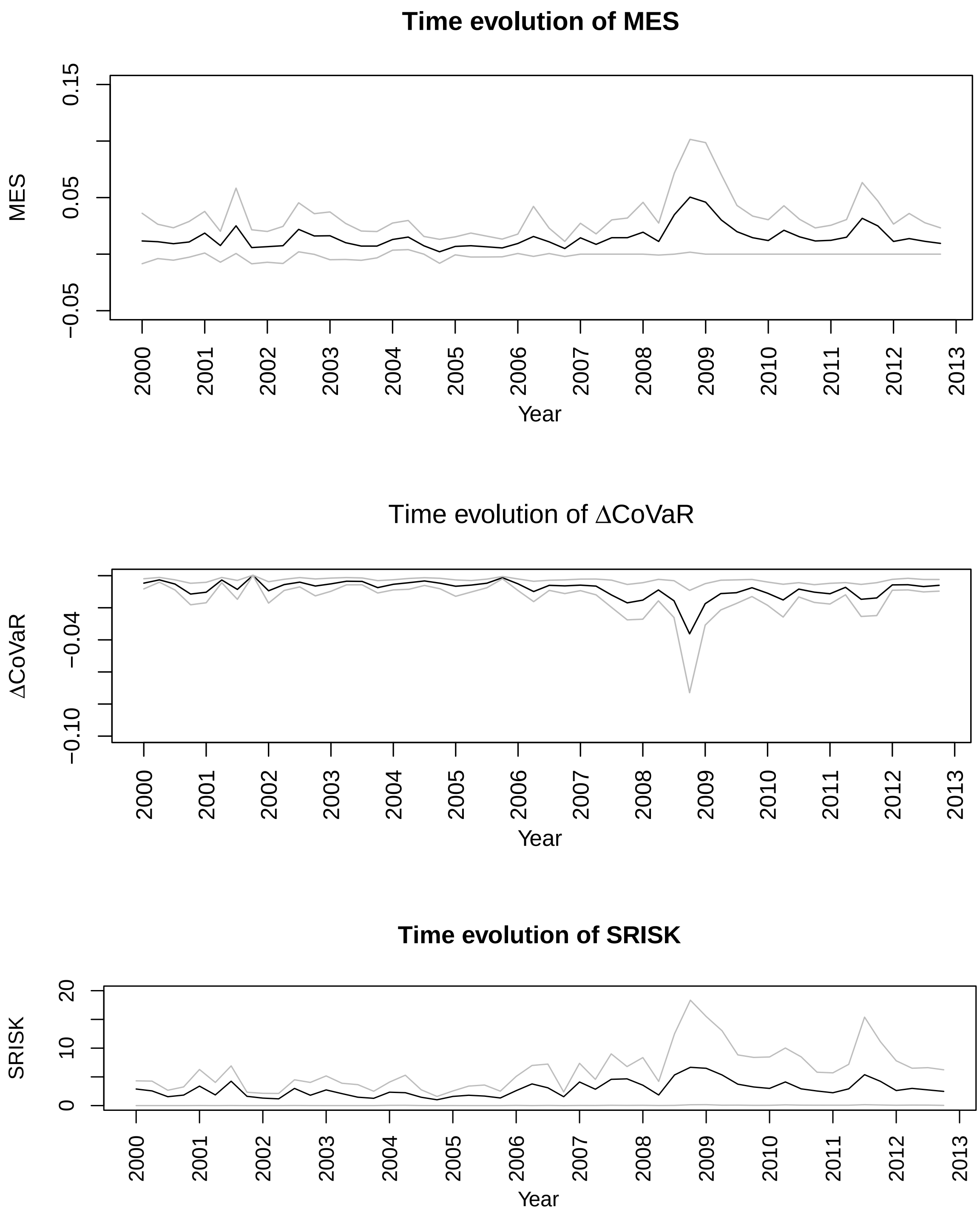

Figure 2: Time evolution of systemic risk measures for (systemically relevant) insurers in the period from 2000 to 2012.

This figure plots the evolution of the systemic risk measures Marginal Expected Shortfalls (MES), SRISK, and ΔCoVaR over a sample period from 2000 to 2012. The sample consists of 253 international life and non-life insurers. In each plot, the mean of the respective risk measure in each quarter is given for a sample of 253 international insurers (yellow shaded area) and for the nine insurers identified as global systemically important by the IAIS (2012) (black bars). All data are winsorized at the 1% level. Variables and data sources are defined in Appendix A.2.

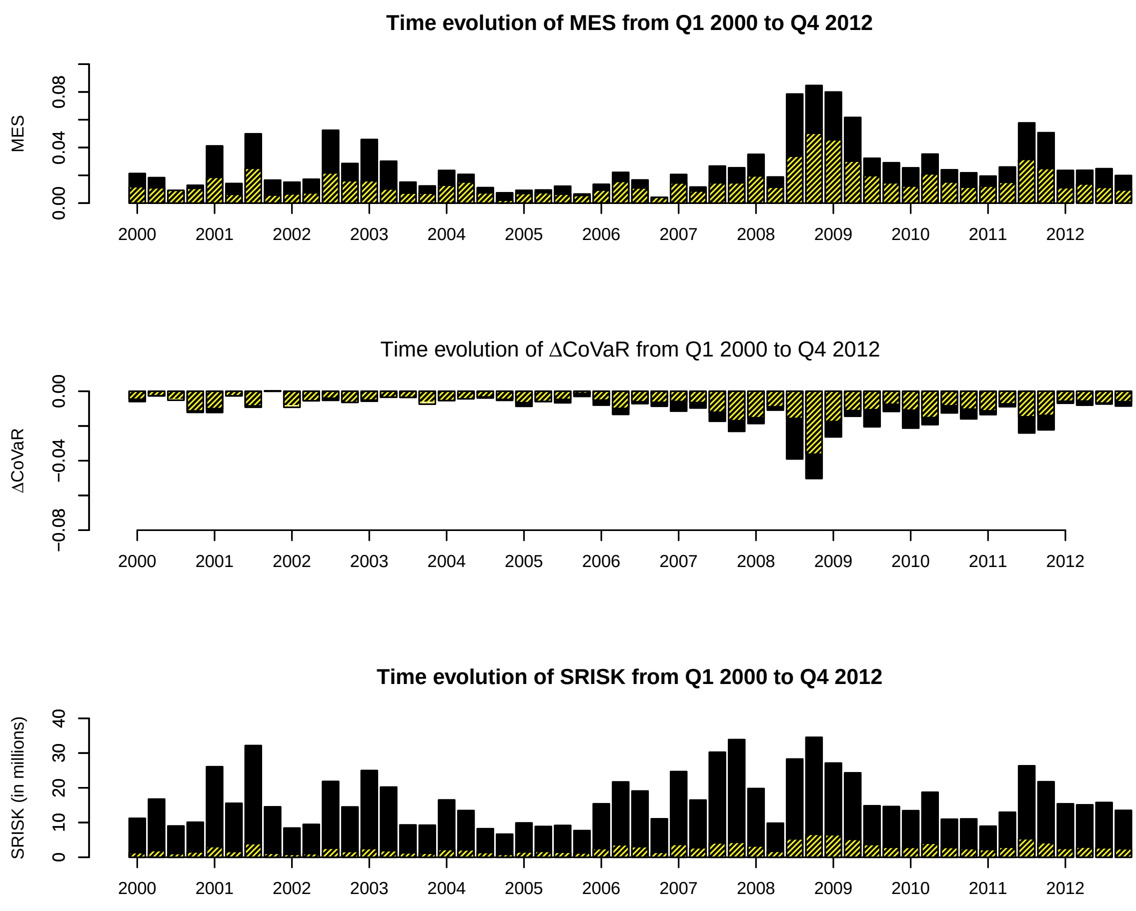

Figure 3: Time evolution of CATFIN.

This figure plots the time evolution of the CATFIN measure introduced in Allen et al. (2012). CATFIN is calculated by averaging the three Value-at-Risk estimates from the Generalized Pareto Distribution, the Skewed Generalized Error Distribution, and the nonparametric sample quantiles for the cross-section of stock returns of financial institutions in excess of the 1-month treasury bill rate. The red line represents the CATFIN measure for the cross section of insurers in our sample and the black line is the original CATFIN measure calculated in Allen et al. (2012) taken from the authors' website at http://faculty.msb.edu/tgb27/workingpapers.html. The sample used for calculating the CATFIN of the insurance sector consists of 253 international life and non-life insurers.

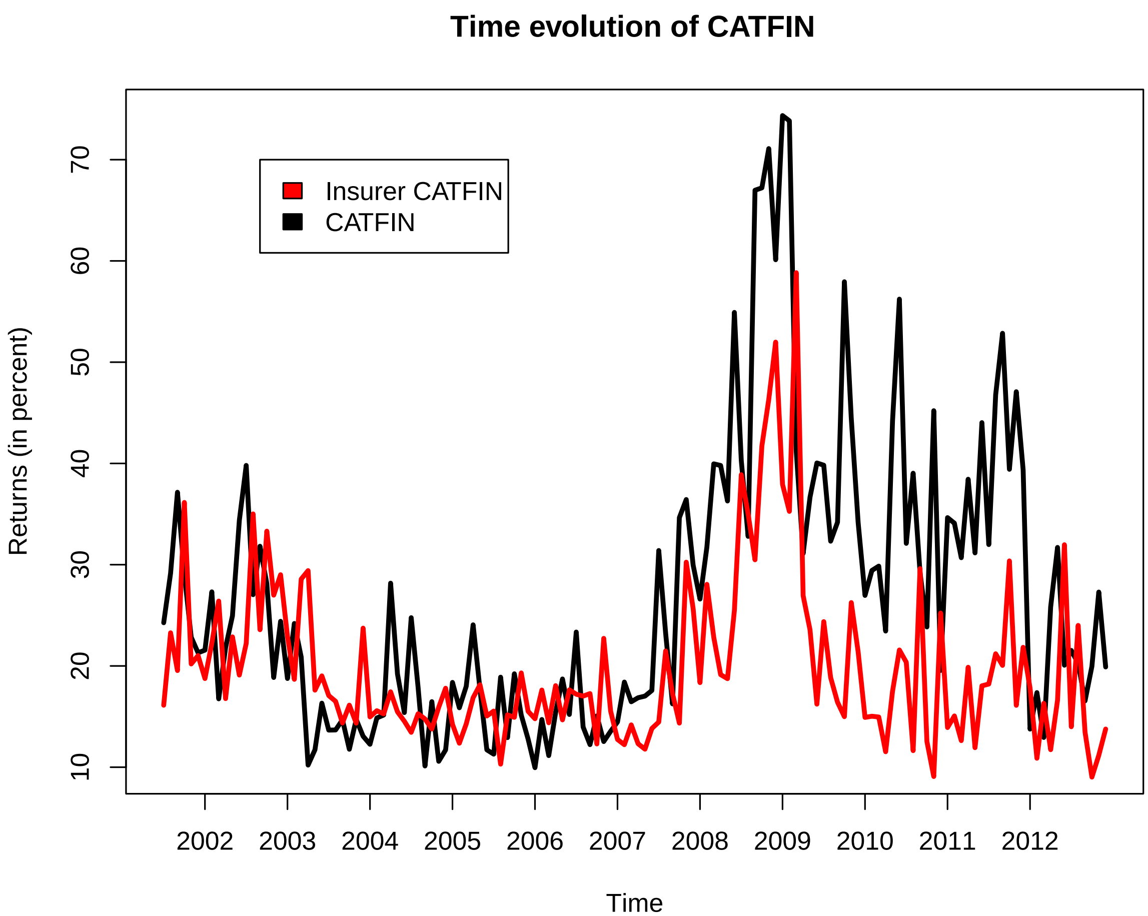

Table I: Descriptive statistics.

The table presents descriptive statistics of the quarterly estimates of different systemic risk measures for a sample of 253 international insurers. The sample period runs from Q1 2000 to Q4 2012. Additionally, the table presents descriptive statistics for our set of explanatory variables. We report the number of observations, minimum and maximum values, percentiles and moments. All variables and data sources are defined in Appendix A.2.

			Percentiles							Moments			
	Obs	Min	1th	5th	20th	80th	95th	99th	Max	Mean	St. Dev.	Skewness	Kurtosis
MES	12,808	-0.11	-0.02	-0.01	0.00	0.02	0.05	0.09	0.45	0.01	0.02	3.44	35.53
ΔCoVaR	4,893	-0.12	-0.04	-0.02	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	-3.90	29.98
SRISK (in billions)	8,997	0.00	0.00	0.00	0.07	2.46	12.30	42.09	166.22	2.80	8.50	7.56	81.36
Interconnectedness	11,361	0.00	0.00	0.00	0.00	0.16	2.37	123.99	399,010.80	386.98	8,929.08	29.26	982.91
Total assets (in billions)	10,998	0.02	0.59	1.18	29.03	61.37	331.62	865.13	2,076.19	65.63	165.79	5.40	38.05
Leverage	12,066	1.01	1.32	1.77	3.10	13.37	30.41	86.80	44,180.69	30.27	819.12	52.16	2,796.82
Debt maturity	11,104	0.00	0.00	0.00	0.58	1.00	1.00	1.00	1.00	0.78	0.32	-1.45	0.78
Foreign sales	7,131	-63.41	0.00	0.00	0.00	50.42	82.85	109.82	202.64	23.63	30.11	1.23	1.26
Investment success	12,065	-22.10	0.04	0.23	0.59	0.89	0.95	1.03	4.13	0.71	0.49	-34.67	1,614.19
Loss ratio	11,994	-1,717.91	3.39	38.53	64.26	109.65	196.19	770.70	8,439.29	107.48	211.37	20.09	681.64
Market-to-book	12,038	-14.10	0.26	0.55	0.91	2.27	4.16	7.49	45.12	1.78	1.67	8.32	167.10
Non-policyholder liabilities	12,025	0.56	1.01	1.05	1.12	1.70	4.78	35.67	1,144.63	4.03	35.51	21.25	524.18
Operating expenses	12,510	-0.18	0.01	0.05	0.11	0.32	0.54	0.78	1.39	0.23	0.16	2.06	7.81
Other income (in millions)	12,669	-4.87	-0.93	-0.10	-0.00	0.01	0.17	1.19	17.95	0.02	0.53	0.00	0.00
ROA	12,423	-30.22	-5.56	-1.09	0.39	3.44	6.94	10.90	38.08	1.88	3.22	1.30	30.09
Performance	12,744	-0.91	-0.43	-0.25	-0.09	0.12	0.30	0.57	10.64	0.02	0.21	11.83	559.55
Net Revenues (in billions)	10,954	0.00	0.08	0.26	0.73	11.40	44.61	105.30	172.37	9.70	19.15	3.95	18.57
ROE	9,853	-77.86	-66.22	-6.84	5.66	16.29	25.82	34.29	36.69	10.16	12.84	-3.39	19.27
GDP Growth	12,598	-8.54	-5.49	-3.11	0.81	4.10	5.54	9.30	14.78	2.21	2.57	-0.45	2.25
Inflation	12,598	-14.45	-2.22	-1.20	0.88	3.12	6.01	8.86	27.57	2.15	2.16	1.49	12.38
Stock market turnover	12,648	0.15	1.99	6.80	63.14	189.07	348.58	404.07	404.07	130.21	85.64	1.17	1.78

Table II: Descriptive statistics for main variables of interest: life and non-life insurer.

The table compares the characteristics of insurers in the life insurance sector relative to those in the non-life sector. Our sample consists of 253 international insurers (listed in Appendix A.1) and covers the period from Q1 2000 to Q4 2012 (Panel A) and from Q3 2008 to Q2 2009 (Panel B). We report the minimum, maximum, mean, 5%- and 95%-quantiles, and the standard deviation of the variables. The equality of means of the different variables is tested using Welch's t test for unequal sample sizes and possibly unequal variances of the two samples. All variables and data sources are defined in Appendix A.2. ***,**,* denote estimates that are significant at the 1%, 5%, and 10% level, respectively.

	Non-life							Life							
	No. obs.	Min	25%	Mean	75%	Max	St. dev.	No. obs.	Min	25%	Mean	75%	Max	St. dev.	t-statistic
Panel A: Q1 2000 - Q4 2012															
MES	6,386	-0.082	0.003	0.014	0.019	0.452	0.020	4,991	-0.047	0.004	0.016	0.023	0.304	0.020	-7.274***
ΔCoVaR	2,272	-0.119	-0.009	-0.007	-0.003	0.001	0.010	1,582	-0.089	-0.010	-0.008	-0.003	0.001	0.010	2.331**
SRISK (in billions)	5,150	0.000	0.103	3.210	1.718	1.662	10.280	3,847	0.000	0.108	2.242	1.836	79.23	5.190	5.842***
Interconnectedness	6,462	0.000	0.000	679.690	0.100	399,010.800	11,831.450	4,899	0.000	0.000	0.879	0.095	350.900	9.680	4.612***
Total assets (in billions)	6,180	0.02	2.75	43.00	24.13	1,483.00	134.65	4,818	0.11	7.22	94.66	93.28	2,076.00	194.91	-15.71***
Leverage	5,974	1.01	2.89	16.01	8.61	7,100.00	200.04	4,588	1.25	6.25	56.52	16.22	44,180.00	1,308.26	-2.08**
Panel B: Q3 2008 - Q2 2009															
MES	520	-0.032	0.012	0.034	0.049	0.195	0.031	388	-0.032	0.009	0.040	0.059	0.227	0.039	-2.591***
ΔCoVaR	109	-0.100	-0.021	-0.018	-0.006	-0.001	0.017	84	-0.089	-0.024	-0.020	-0.009	-0.003	0.019	0.957
SRISK (in millions)	369	0.000	0.440	5.988	4.863	88.650	13.040	262	0.000	0.376	4.970	5.156	79.230	9.330	1.144
Interconnectedness	529	0.000	0.000	773.100	0.070	294,900.000	13,698.390	405	0.000	0.000	0.001	1.205	0.098	202.800	10.710
Total assets (in billions)	443	0.16	3.63	47.89	27.45	1476.00	143.59	328	0.73	12.38	126.30	125.90	2,076.00	248.28	-5.12***
Leverage	443	1.32	3.02	11.67	9.88	210.60	23.42	322	1.50	7.18	297.00	22.93	44,180.00	3,475.01	-1.47

Table III: Descriptive statistics for main variables of interest: Global Systemically Important Insurers.

This table shows the respective descriptive statistics for the nine global systemically important insurers (G-SIIs) as defined by the international association of insurance supervisors (IAIS) in the period from Q1 2000 to Q4 2012 (Panel A) and from Q3 2008 to Q2 2009 (Panel B). The nine G-SIIs are Allianz, American International Group, Assicurazioni Generali, Aviva, Axa, MetLife, Ping An Insurance (Group) Company of China, Prudential Financial and Prudential. All variables and data sources are defined in Appendix A.2.

	G-SIIs						
	No. obs.	Min	25%	Mean	75%	Max	St. dev.
Panel A: Q1 2000 - Q4 2012							
MES	434	-0.001	0.011	0.028	0.035	0.452	0.031
ΔCoVaR	249	-0.119	-0.014	-0.011	-0.004	0.000	0.012
SRISK (in billions)	378	0.000	2.065	18.209	27.387	125.494	21.956
Interconnectedness	460	0.000	0.000	0.352	0.094	30.800	1.785
Total assets (in billions)	424	24.55	293.00	521.20	730.90	1483.00	315.38
Leverage	416	1.36	3.71	10.69	14.67	55.08	10.76
Panel B: Q3 2008 - Q2 2009							
MES	36	0.000	0.035	0.065	0.090	0.169	0.042
ΔCoVaR	20	-0.100	-0.039	-0.028	-0.012	-0.008	0.025
SRISK (in billions)	28	0.037	6.544	25.198	36.902	79.229	24.351
Interconnectedness	32	0.000	0.000	0.113	0.037	0.850	0.239
Total assets (in billions)	32	107.80	438.20	615.00	844.80	1476.20	330.19
Leverage	32	2.918	16.909	42.930	32.141	210.612	62.609

Table IV: Baseline panel regressions.

This table shows the results of panel regressions of quarterly estimates of three systemic risk measures for a sample of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors on the country level. The estimated model is:

$$\begin{aligned} SystemicRisk_{i,t} = \beta_0 &+ \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} + \beta_3 \cdot Total\ assets_{i,t-2} \\ &+ \Omega \cdot Insurer\ controls_{i,t-2} + \Theta \cdot Country\ controls_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables. The sample includes insurer-quarter observations of 112 international life insurers and 141 international non-life insurers over the time period Q1 2000 to Q4 2012. P-values are reported in parentheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table A.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable:	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK
Sample:	Life	Non-Life	Life	Non-Life	Life	Non-Life
	(1)	(2)	(3)	(4)	(5)	(6)
Interconnectedness	11.6000	2.6100***	-11.7000	0.0078**	-2132.9000	7.0100**
	(0.728)	(0.002)	(0.308)	(0.011)	(0.556)	(0.047)
Total assets	-0.0030	0.0005	0.0049*	-0.0004	1.0075*	5.5704**
	(0.216)	(0.568)	(0.051)	(0.820)	(0.094)	(0.016)
Leverage	-0.0001*	-0.0002***	0.0002*	0.0004***	-0.0072	-0.1228***
	(0.056)	(0.000)	(0.094)	(0.000)	(0.443)	(0.000)
Debt maturity	-0.0011	-0.0006	0.0019	0.0009	0.0754	-3.1216*
	(0.403)	(0.485)	(0.309)	(0.580)	(0.837)	(0.097)
Investment success	0.0008	-0.0067	-0.0049***	0.0091	-0.4141	-2.1429
	(0.652)	(0.281)	(0.004)	(0.221)	(0.434)	(0.484)
Loss ratio	-0.0057	0.0462*	-0.0018	0.0006	0.0544	-1.5115
	(0.183)	(0.067)	(0.128)	(0.898)	(0.666)	(0.156)
Market-to-book ratio	0.0005*	0.0004	-0.0006	0.0002	0.1047	0.0943
	(0.096)	(0.348)	(0.177)	(0.155)	(0.176)	(0.486)
Non-policyholder liabilities	-0.1759**	0.1.1890**	-0.0022	-0.0424	-4.2576***	14.8805
	(0.030)	(0.035)	(0.637)	(0.376)	(0.003)	(0.611)
Operating expenses	-0.0291**	-0.0041	0.0253**	0.0155*	-1.9027	14.5905
	(0.034)	(0.304)	(0.022)	(0.050)	(0.437)	(0.101)
Other income	-0.6770	0.0184	1.4500	-0.0290	267.000	523.000
	(0.226)	(0.875)	(0.441)	(0.947)	(0.521)	(0.461)
ROA	0.2000	0.0405	0.1811	0.0467	15.8181	156.7285
	(0.649)	(0.802)	(0.512)	(0.820)	(0.693)	(0.147)
Performance	-0.0012	0.0011	-0.0027	-0.0001	-0.3072	0.1843
	(0.409)	(0.471)	(0.158)	(0.966)	(0.165)	(0.726)
GDP growth	0.0003	0.0002	-0.0002	0.0002	-0.0796	-0.0908
	(0.150)	(0.365)	(0.516)	(0.499)	(0.150)	(0.424)
Inflation	-0.0001	-0.0001	-0.0004*	-0.0011***	-0.0269	-0.2008*
	(0.397)	(0.750)	(0.074)	(0.002)	(0.648)	(0.051)
Stock market turnover	0.0023	-0.0108	0.0460***	0.0452***	1.9347	26.7704***
	(0.801)	(0.225)	(0.008)	(0.003)	(0.520)	(0.000)
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	925	1,333	2,658	3,569	2,508	3,426
Adj. R^2	0.5865	0.5752	0.4422	0.4225	0.2040	0.1412

Table V: Panel regressions - Large insurers.

This table shows the results of panel regressions of quarterly estimates of three systemic risk measures for a sample of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors on the country level. The estimated model is:

$$SystemicRisk_{i,t} = \beta_0 + \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} + \beta_3 \cdot Total\ assets_{i,t-2} + \Omega \cdot Insurer\ controls_{i,t-2} + \Theta \cdot Country\ controls_{i,t-1} + \varepsilon_{i,t}$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables. The sample includes insurer-quarter observations of 112 international life insurers and 141 international non-life insurers over the time period Q1 2000 to Q4 2012. In contrast to our baseline setting, in these regressions, we only use insurer-quarters of insurers in the top total assets quartile. P-values are reported in parantheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table A.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable:	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK
Sample:	Life	Non-Life	Life	Non-Life	Life	Non-Life
	(1)	(2)	(3)	(4)	(5)	(6)
Interconnectedness	1.1058	-0.2942**	0.0017	0.4796	0.3641	-205.6195
	(0.179)	(0.023)	(0.120)	(0.112)	(0.337)	(0.500)
Total assets	-0.0008	-0.0037	0.0016	-0.0026	4.6792	11.8426***
	(0.885)	(0.117)	(0.626)	(0.415)	(0.122)	(0.000)
Leverage	0.0001	-0.0001***	0.0004***	0.0003***	-0.0616	-0.0758**
	(0.297)	(0.001)	(0.003)	(0.000)	(0.242)	(0.047)
Debt maturity	-0.0032	0.0032	-0.0007	-0.0082	-1.3610	-19.8851
	(0.243)	(0.292)	(0.867)	(0.208)	(0.330)	(0.105)
Investment success	-0.0114	-0.0347**	0.0174	0.0232	3.8998	-20.3975**
	(0.212)	(0.032)	(0.147)	(0.418)	(0.380)	(0.023)
Loss ratio	-0.1341**	-0.0751*	-0.0090**	0.0359	0.0280	1.9320
	(0.022)	(0.097)	(0.028)	(0.362)	(0.987)	(0.892)
Market-to-book ratio	0.0026**	-0.0013	0.0004	0.0021	-0.4833	8.5890*
	(0.011)	(0.447)	(0.605)	(0.547)	(0.294)	(0.065)
Non-policyholder liabilities	0.4520	-0.9806	0.0398	-0.1975	10.0329	-59.2137
	(0.685)	(0.306)	(0.341)	(0.800)	(0.367)	(0.877)
Operating expenses	0.0220	-0.0730***	0.0331**	0.0722	14.8526	79.9298*
	(0.482)	(0.004)	(0.025)	(0.119)	(0.165)	(0.056)
Other income	3.4200***	0.0539	0.4310	0.1690	3670.0000***	-504.0000
	(0.003)	(0.767)	(0.872)	(0.774)	(0.004)	(0.306)
ROA	-0.6000*	-0.7000	0.5000*	2.0000*	167.0000	993.2000**
	(0.078)	(0.183)	(0.099)	(0.070)	(0.290)	(0.038)
Performance	-0.0046**	0.0047**	-0.0081**	-0.0147***	-0.9752	-2.4596
	(0.037)	(0.024)	(0.013)	(0.005)	(0.132)	(0.298)
GDP growth	0.0000	0.0003	-0.0006	0.0002	-0.2241	-0.6056
	(0.984)	(0.421)	(0.233)	(0.837)	(0.115)	(0.337)
Inflation	-0.0004	-0.0011	0.0005	0.0007	0.6069**	0.7485
	(0.465)	(0.120)	(0.415)	(0.670)	(0.019)	(0.494)
Stock market turnover	-0.0184	-0.0392**	0.0194	0.0629*	-8.2560	68.5784***
	(0.167)	(0.027)	(0.315)	(0.055)	(0.185)	(0.002)
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	377	296	858	560	843	554
Adj. R^2	0.630	0.840	0.556	0.512	0.300	0.395

Table VI: Panel regressions for U.S. and non-U.S. insurers.

This table shows the results of panel regressions of quarterly estimates of three systemic risk measures for a sample of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors on the country level. The estimated model is:

$$
\begin{aligned}
SystemicRisk_{i,t} = \beta_0 \; + \; \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} \; + \; \beta_3 \cdot Total\ assets_{i,t-2} \\
+ \; \Omega \cdot Insurer\ controls_{i,t-2} \; + \; \Theta \cdot Country\ controls_{i,t-1} \; + \varepsilon_{i,t}
\end{aligned}
$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{\,i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables. The samples include insurer-quarter observations of 95 U.S. and 158 non-U.S. insurers over the time period Q1 2000 to Q4 2012. P-values are reported in parentheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table A.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

	US						Non-US					
Dependent variable:	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK
Sample:	Life	Non-Life	Life	Non-Life	Life	Non-Life	Life	Non-Life	Life	Non-Life	Life	Non-Life
Interconnectedness	34.3000	2.8900***	-129.6	0.0072*	645.1000	5.4200*	2.8900***	-6.1100**	0.0072*	0.6020	5.4200*	-142.4000
	(0.470)	(0.000)	(0.295)	(0.085)	(0.810)	(0.064)	(0.000)	(0.041)	(0.085)	(0.771)	(0.064)	(0.833)
Total assets	0.0005	0.0026	0.0070	-0.0021	0.9090	1.6734	0.0026	0.0002	-0.0021	-0.0012	1.6734	6.1613**
	(0.952)	(0.126)	(0.105)	(0.340)	(0.272)	(0.124)	(0.126)	(0.919)	(0.340)	(0.555)	(0.124)	(0.021)
Leverage	0.0002	-0.0002***	0.0001	0.0004***	0.0020	-0.1180***	-0.0002***	-0.0002**	0.0004***	0.0006**	-0.1180***	0.0368
	(0.545)	(0.000)	(0.537)	(0.000)	(0.822)	(0.000)	(0.000)	(0.046)	(0.000)	(0.016)	(0.000)	(0.573)
Other control varialbes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	258	812	723	1,917	678	1,807	812	521	1,917	1,652	1,807	1,619
Adj. R^2	0.589	0.574	0.452	0.540	0.379	0.221	0.574	0.689	0.540	0.377	0.221	0.195

Table VII: Panel regressions for the crisis period

This table shows the results of panel regressions of quarterly systemic risk of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors country level. The conceptual approach is the following:

$$SystemicRisk_{i,t} = \beta_0 + \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} + \beta_3 \cdot Total\ assets_{i,t-2} + \Omega \cdot Insurer\ controls_{i,t-2} + \Theta \cdot Country\ controls_{i,t-1} + \varepsilon_{i,t}$$

The sample includes insurer-quarter observations of 253 international insurers over the time period Q1 2006 to Q4 2010. P-values are reported in parantheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table A.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable:	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK
Sample:	Life	Non-Life	Life	Non-Life	Life	Non-Life
	(1)	(2)	(3)	(4)	(5)	(6)
Interconnectedness	0.6409	0.0405	-0.0316	-0.0316	29.8448	-2.2579
	(0.252)	(0.920)	(0.962)	(0.377)	(0.833)	(0.851)
Total assets	-0.0192	0.0042	-0.0001	-0.0072	3.9042	6.9138**
	(0.269)	(0.539)	(0.994)	(0.537)	(0.214)	(0.016)
Leverage	0.0002	-0.0003***	0.0005	0.0006***	0.2112	-0.0841***
	(0.480)	(0.000)	(0.254)	(0.000)	(0.180)	(0.000)
Debt maturity	-0.0146	-0.0049	0.0015	0.0061	-2.0916	1.1335
	(0.226)	(0.274)	(0.774)	(0.251)	(0.547)	(0.684)
Investment success	-0.0281	-0.0585**	-0.0127	-0.0016	-6.1390	-0.5964
	(0.316)	(0.020)	(0.555)	(0.722)	(0.439)	(0.581)
Loss ratio	-0.0595	0.0016	0.0342	0.0004	-9.6110*	-1.0701*
	(0.432)	(0.979)	(0.298)	(0.941)	(0.062)	(0.057)
Market-to-book ratio	0.0011	-0.0003	-0.0002	0.0000	-1.4385	-0.0573
	(0.686)	(0.732)	(0.930)	(0.754)	(0.305)	(0.471)
Non-policyholder liabilities	-10.8000***	-1.7117	0.5478	-0.1793	-702.6164	13.0993
	(0.001)	(0.233)	(0.764)	(0.340)	(0.370)	(0.787)
Operating expenses	0.0157***	-0.0061	0.0031	0.0187	5.1510	-1.1348
	(0.005)	(0.476)	(0.820)	(0.316)	(0.538)	(0.796)
Other income	14.3000	1.8100	-15.8000	0.2190	-130.0000	60.0000**
	(0.224)	(0.429)	(0.182)	(0.970)	(0.597)	(0.021)
ROA	-0.9207	-3.4268**	0.3275	0.5115	77.5754	67.3172
	(0.776)	(0.023)	(0.549)	(0.559)	(0.628)	(0.422)
Performance	-0.0091**	-0.0031	0.0088	0.0004	2.4556**	4.7450
	(0.024)	(0.294)	(0.356)	(0.947)	(0.046)	(0.180)
GDP growth	0.0003	-0.0002	0.0011	0.0007	0.1959	0.3530
	(0.770)	(0.753)	(0.243)	(0.328)	(0.373)	(0.517)
Inflation	0.0004	0.0019	-0.0003	-0.0024	0.2310	-0.4832*
	(0.656)	(0.107)	(0.801)	(0.143)	(0.320)	(0.058)
Stock market turnover	0.0085	-0.0319*	0.0667**	0.0590**	4.2736	34.6236**
	(0.679)	(0.068)	(0.018)	(0.035)	(0.654)	(0.012)
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130	239	387	788	379	772
Adj. R^2	0.787	0.847	0.575	0.470	0.244	0.155