The Contribution of Shadow Insurance to Systemic Risk*

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Abstract

Shadow insurance is a regulatory loophole exploited by certain insurance groups to increase risk exposure, potentially destabilising the financial system. In this paper, we evaluate the contribution of shadow insurance to systemic risk of the global financial sector using a sample of 215 international insurance entities covering the 2004–2017 period. We detect shadow insurance by examining every reinsurance agreement on the Schedule S filings. Using both $\Delta CoVaR$ and $SRISK$ measures, we find that the practice of shadow insurance is a significant driver of global systemic risk.

Keywords: Financial stability; Interconnectedness; Shadow banking activity; Size.
JEL Classification: G01; G22; G23.

*We wish to thank participants in the conference on "Systemic Risk, Banking and Insurance, and the Role of their Shadow Entities" (London, 4th October 2019) and the 31st Asian Finance Association Annual Meeting (Ho Chi Minh, 7th–9th July 2019) for useful comments and suggestions. Special thanks to Thorsten Beck, Peter Cincinelli and Robin Lumsdaine for helpful feedback on a previous version of this paper. We are grateful to the Editor, Iftekhar Hasan, and two anonymous Referees for extremely detailed and constructive feedback. The usual disclaimer applies. Soon Heng Leong acknowledges support from the Centre for Econometric Analysis and Cass Business School, City University of London, for financing the "2017/2021 PhD Studentship in Memory of Ana Timberlake".

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August 3, 2020

1. Introduction

The main objective of this paper is to assess the contribution of shadow insurance to systemic risk of the global financial sector. To this aim, we use a sample of 215 public insurance entities across 40 countries over the period 2004–2017. To detect shadow activities, we examine all reinsurance agreements from the Schedule S filings. To measure interconnectedness between the insurance and banking sectors, we analyse an additional sample of 745 traditional banks. On the basis of both $\Delta CoVaR$ and $SRISK$ systemic risk measures, we find statistically significant evidence that the practice of shadow insurance affects the stability of global financial system.

In recent years, the financial stability literature has proposed a large number of systemic risk measures. A comprehensive review is provided by Benoit et al. (2017), who distinguish measures that study sources of systemic risk from global approaches that could support a more efficient regulation. The prominent global measures are the $\Delta CoVaR$ of Adrian and Brunnermeier (2016), the $SRISK$ of Acharya et al. (2012) and Brownlees and Engle (2016), the marginal expected shortfall (MES) and systemic expected shortfall (SES) of Acharya et al. (2017). These measures have been used extensively to identify determinants that drive systemic risk, with more emphasis on the banking sector. For instance, López-Espinosa et al. (2012) use $\Delta CoVaR$ to study a sample of 54 large international banks to find that short-term wholesale funding increases systemic risk. Adrian and Brunnermeier (2016) study the systemic relevance of all publicly listed financial entities in the United States to find that leverage, maturity mismatch and size are the main drivers of systemic risk. Brownlees and Engle (2016) employ $SRISK$ to find that major banks such as Bear Stearns, Fannie Mae, Freddie Mac, Lehman Brothers and Morgan Stanley play a significant role in systemic risk contribution. Using both $\Delta CoVaR$ and $SRISK$, Laeven et al. (2016) study a panel of 412 large banks from 56 countries to find that systemic risk grows with bank size. Abedifar et al. (2017) combine both Islamic and conventional financial entities to find that traditional banks with Islamic windows are highly interconnected during the subprime financial crisis.

The aforementioned literature revolves around the financial sector or the banking industry, with minimal emphasis on the insurance sector. Traditionally, insurance entities are not deemed to be of systemic relevance to destabilise the greater financial system. Unlike banks, insurers are not subject to a bank run and therefore do not face the potential of sudden liquidity risk. However, the bailout of American Insurance Group (AIG) in 2008 suggests otherwise. Using MES, $SRISK$ and $\Delta CoVaR$, Bierth et al. (2015) analyse the exposure and contribution of 253 international insurance entities to systemic risk between 2000 and 2012. The authors find that interconnectedness with the financial system increases insurers' systemic risk exposure and highly levered entities contribute more to systemic risk. The authors, however, do not address the role played by shadow insurance.

The risk profile of insurance entities becomes increasingly complicated when they practice shadow insurance to move blocks of liability to affiliated reinsurers. Koijen and Yogo (2016) define shadow insurance as "*reinsurance ceded to affiliated and unauthorised reinsurer without A.M. Best rating*". In this paper, we adopt a more stringent definition by also considering Fitch, Moody's and S&P ratings. In a typical shadow insurance deal, a parent insurance entity first sets up a "captive" subsidiary, which is essentially a shell company that is often located offshore with a looser reserve requirement. The shell entity is usually unauthorised to sell insurance to third parties, and its primary function is to re-insure the parent company. Next, an operating entity belonging to the company group cedes a portion of existing liability to the subsidiary. Consequently, the insurance group can reduce its risk-based capital to underwrite more contracts. By practising shadow insurance, a "shadow insurer" could increase its risk exposure to drive potential return. We define *shadow insurer* as the ultimate parent company of an insurance group practising shadow insurance.

Lawsky (2013) describes shadow insurance as "*a little-known loophole that puts insurance policyholders and taxpayers at greater risk*", and suggests that the practice of shadow insurance could disrupt the stability of the entire financial system. Schwarcz (2015) conjectures that shadow insurance could increase the interconnectedness between the insurance and banking sectors, thus driving systemic risk. Using A.M. Best rating of insurance entities, Koijen and Yogo (2016) propose a theoretical framework to estimate the term structure of default probabilities of a company practising shadow insurance. Under plausible assumptions, the authors show that an entity using shadow insurance is three and a half times more likely to default over ten years. Koijen and Yogo (2017) document that a large portion of shadow insurance is funded through letters of credit, which is mostly written by banks. These documentations suggest further that there is a remarkable level of interconnectedness between the shadow insurance business and the entire banking system, which raises systemic concern.

In this paper, we empirically examine the contribution of shadow insurance to systemic risk of the global financial industry. To this aim, we collect all reinsurance agreements from the National Association of Insurance Commissioners (NAIC) Schedule S filings to identify 29 publicly listed shadow insurers. We also document that about 2.8 cents every dollar ceded were shadow in 2004 with the amount growing substantially to 21 cents every dollar in 2017. For a global study, we include all publicly listed insurance entities across the world as our main sample. To measure the interconnectedness between our sample insurers and the banking industry, we employ the principal component measure proposed by Billio et al. (2012). In particular, we compute the interconnectedness between our main sample and the banking system by further considering all publicly listed banks available in *Datastream*.

In terms of systemic risk measures, we employ the prominent global measures $\Delta CoVaR$ of Adrian and Brunnermeier (2016) and $SRISK$ of Acharya et al. (2012) and Brownlees and Engle (2016). We do not use the MES measure because it is proportional to market beta that captures only systematic risk (Benoit et al., 2017, p. 136–137). Conversely, $SRISK$ is less related to beta because it also depends on the debt and market capitalisation of an entity. Although Benoit et al. (2017) show that the dynamics of $\Delta CoVaR$ matches value-at-risk (VaR) in the time series dimension, there is only a weak relationship between them in the cross-sectional dimension. An entity might not be risky individually with a low VaR, but it could be of significant systemic relevance as indicated by a high $\Delta CoVaR$. On the one hand, $\Delta CoVaR$ measures the VaR of the financial system, conditional on an insurer being in distress. On the other hand, $SRISK$ evaluates the expected shortfall (ES) of an insurance entity, conditional on a distressed financial system.

Both $\Delta CoVaR$ and $SRISK$ measures quantify the contribution of an entity to systemic risk of the financial system. However, Benoit et al. (2013) show that $\Delta CoVaR$ and $SRISK$ do not provide similar systemic rankings unless under certain strict conditions such as the correlation with the financial system of riskier insurers is always higher than that of less risky entities. Moreover, Zhang et al. (2015) find that $\Delta CoVaR$ is more reactive to the subprime financial crisis than other popular measures including $SRISK$. To accommodate the distinct features of the employed measures, we analyse both the full sample period and a subsample that focuses on the period of financial distress.

From the descriptive statistics, we find that shadow insurers are typically larger, riskier, more interconnected with other market participants and more likely to contribute to financial instability compared with non-shadow entities. Next, we perform panel analyses to examine the hypothesis that the practice of shadow insurance increases systemic risk of the global financial system, after controlling for factors such as the magnitude of shadow insurance, size of the entity and its degree of interconnectedness with the banking system. In line with the theory and regulatory expectations, our findings confirm the pivotal role played by size and interconnectedness in the spreading of systemic risk. We also find that the practice of shadow insurance increases systemic risk, with $\Delta CoVaR$ showing a stronger effect during distress period and $SRISK$ suggesting a more profound long-run impact. Overall, our results suggest that shadow insurance poses non-trivial risks to the financial system, which confirms the main hypothesis of the paper.

The remainder of this paper is organised as follows. In Section 2, we describe the data and methodology used in the study. Section 3 presents the results of our analysis. Section 4 concludes.

2. Data, variables and methodology

In this section, we present the procedures outlining the preparation of our dataset and the detection of shadow activities. We describe the formulation of our systemic risk measures, which serve as the main dependent variables, and introduce the explanatory and control variables involved in the study. Finally, we summarise all of the variables.

2.1. Data preparation

We select all public and active insurance entities that are available in *Datastream*. Next, we select entities that are continuously listed between 2004Q1 and 2017Q4, leading to a total of 56 quarters for the analysis. We focus on primary issues and therefore we exclude secondary listings from the selection. Insurers with unavailable share price and total asset data are omitted. Insurance entities with zero share price data are further excluded. We also exclude entities whose daily share price does not fluctuate for more than a quarter. With this filter, we obtain a sample of 215 insurers across 40 countries. Missing data points of a few entities are estimated using the nearest observation. Lastly, we collect the data in US dollar to minimise potential bias due to currency risk. In Table 1, we report the number of entities by country in our main sample. Given that United States is the leading country in the global financial industry, it is not surprising that its entities make up about a quarter of our sample. The names and *Datastream Mnemonics* of the full sample are reported in a supplementary document that is available upon request to the authors. Fig. 1 plots the market capitalisation of our sample. We observe that the global insurance industry was growing steadily until the subprime mortgage crisis in 2008 that saw a sharp decline in the market value of the sector. After the financial crisis, the industry remained stagnant for a few years, and it began to grow gradually from 2012.

[Table 1 and Fig. 1 about here]

2.2. Shadow insurance

To detect shadow insurance, we collect current and past reinsurance agreements from the Schedule S filings, available to us through *Market Intelligence*. As of April 2018, we have collected a total of 195,717 reinsurance contracts. In each agreement, we observe the name of the operating entity, the name of the ultimate parent company of the operating entity, the name of the reinsurer and the amount of reinsurance ceded to the reinsurer.[1] Moreover,

[1]Following Koijen and Yogo (2016), we define reinsurance ceded as the sum of reserve credit taken and modified coinsurance reserve ceded.

we observe whether the reinsurance is authorised, whether the reinsurer is affiliated with the ceding entity and whether it is rated.[2]

Fig. 2 summarises the growth of the reinsurance industry. We observe that reinsurance has become increasingly popular in the insurance sector as a practice to transfer risks and liabilities to other parties. The amount grew nearly two and a half times from about \$550 billion in 2004 to about \$1300 billion in 2017. Fig. 3 reveals the dollar amount of shadow insurance ceded in the industry. We observe an upward trend in the practice of shadow insurance, growing considerably from about \$15 billion in 2004 to over \$250 billion in 2017. In particular, about 2.8 cents every dollar ceded was shadow in 2004 with this figure rising significantly to 21 cents every dollar in 2017. Overall, we observe a substantial increase in the practice that is used to artificially boost risk-based capital buffers reported to the regulators.

[Fig. 2 and Fig. 3 about here]

Fig. 4 disentangles shadow insurance practised by those belonging to a public parent company from the non-public counterpart. The plot reveals that a large portion of shadow insurance business involves entities that belong to publicly listed shadow insurers. This finding conveniently allows us to analyse the balance sheet data of these shadow insurers using prominent global systemic risk measures such as $\Delta CoVaR$ and $SRISK$ to evaluate the impact of shadow insurance on global financial stability. In the following, we refer to publicly listed shadow insurers simply as shadow insurers.

[Fig. 4 about here]

We identify a total of 29 shadow insurers by scrutinising every reinsurance agreement from the Schedule S filings for the period 2004–2017.[3] We report the names of these shadow entities, their corresponding locations and the extent to which they are involved in shadow insurance in Table 2. Particularly, we compute the shadow index to measure how aggressive an entity participates in shadow activity. The shadow index is computed as the ratio of total shadow insurance to the average reserve held. A high shadow index suggests high

[2] An authorised reinsurer is subject to the same capital requirement as the ceding entity.

[3] In the main analysis, we omit 7 of the 29 shadow insurers due to them being relatively new companies and lack sufficiently long historical data. The omitted entities are Brighthouse Financial, Inc., Dai-ichi Life Holdings, Inc., FGL Holdings, Genworth Financial, Inc., National General Holdings Corporation, Primerica, Inc. and Voya Financial Inc. Although Voya Financial Inc. was recently listed in 2013, the entity was an operating subsidiary under ING Group. Hence, we include ING Group as shadow insurer to obtain 23 shadow insurers in total. The magnitude of shadow insurance practised by the omitted entities is relatively small, and we keep a significant portion of shadow insurance in the analysis. Specifically, the omitted amount represents 6.7% of the total shadow insurance.

aggressiveness as the shadow activities have been carried out with a low insurance reserve on average. For instance, although the dollar amount of shadow insurance practised by MetLife, Inc. ($238,144 million) is higher than Unum Group ($181,381 million), the latter, however, has been engaging the shadow business with higher risk exposure. This is revealed by a shadow index of 4154 from Unum Group compared with 700 from MetLife, Inc.

[Table 2 about here]

2.3. Dependent variables: $\Delta CoVaR$ and $SRISK$

The $\Delta CoVaR$ measure of Adrian and Brunnermeier (2016) makes use of the value-at-risk (VaR). The $q\%$-VaR is the expected maximum dollar loss within the $q\%$ confidence level. Formally, the $q\%$-VaR of an entity i, denoted by VaR_i^q is given by:

$$\mathbb{P}(X_i \leqslant VaR_i^q) = q\% \tag{1}$$

where X_i is the stock return of entity i. We employ historical simulation method to estimate VaR_i^q. In particular, we compute VaR_i^q for a given quarter t using daily stock returns observed in that quarter, scaled using the root-T rule. The computation is repeated for every quarter to obtain a time-varying quarterly VaR_{it}^q series.

Next, $CoVaR$ is defined as the VaR of the financial system conditional on some event $C(X_i)$ on entity i. Formally, $CoVaR^q_{m|C(X_i)}$ is defined by the q-th quantile of the conditional probability distribution:

$$\mathbb{P}\Big(X_m | C(X_i) \leqslant CoVaR^q_{m|C(X_i)}\Big) = q\% \tag{2}$$

where X_m is the return of the global financial system, computed using the *MSCI World Financials Index*.[4] An entity's contribution to systemic risk is measured by $\Delta CoVaR$, namely the difference between $CoVaR$ conditional on the entity being in distress and $CoVaR$ in the median state of the entity. As far as the estimation method is concerned, we follow Adrian and Brunnermeier (2016) to employ quantile regressions to estimate $CoVaR$.

The estimate of the $q\%$-quantile of X_m given the value of X_i is given by:

$$\hat{X}^q_{mt|X_{it}} = \hat{\alpha}_i^q + \hat{\beta}_i^q X_{it} \tag{3}$$

where $\hat{\alpha}_i^q$ and $\hat{\beta}_i^q$ are obtained by performing $q\%$-quantile regression of X_{mt} on X_{it}. From the

[4] Our conclusions remain unchanged if we use an alternative *FTSE World Financials Index*.

definition of VaR in (1), we have that:

$$VaR^q_{mt|X_{it}} = \hat{X}^q_{mt|X_{it}} \tag{4}$$

Using predicted value of $X_{it} = VaR^q_{it}$ yields the $CoVaR^q_{it}$ measure. More formally, within the quantile regression framework, the $CoVaR^q_{it}$ measure is:

$$CoVaR^q_{it} = VaR^q_{mt|X_{it}=VaR^q_{it}} = \hat{\alpha}^q_i + \hat{\beta}^q_i VaR^q_{it} \tag{5}$$

The $\Delta CoVaR$ of entity i for a given quarter t is given by:

$$\Delta CoVaR_{it} = CoVaR^q_{it} - CoVaR^{50}_{it} = \hat{\beta}^q_i (VaR^q_{it} - VaR^{50}_{it}) \tag{6}$$

To simplify the notation, in the following q is always set to be 5%, so that $CoVaR_{it}$ identifies the system losses predicted on the 5%-VaR of entity i, while $\Delta CoVaR_{it}$ identifies the deterioration in the system, when entity i moves from its median state to its 5% worst scenario.

The $SRISK$ measure of Acharya et al. (2012) and Brownlees and Engle (2016) is based on the notion of expected shortfall (ES). Formally, the conditional ES of a system with N financial entity at time t is defined as:

$$ES_{mt} = -\sum_{i=1}^{N} w_{it} \mathbb{E}_{t-1} \big[R_{it} | R_{mt} < C \big] \tag{7}$$

where C is a threshold, and it is set to be the worst 5% daily return of the global financial system R_{mt} in each quarter, R_{it} is entity i's stock return, and w_{it} is the weight of entity i. As in $\Delta CoVaR$, we use the return of *MSCI World Financials Index* as a proxy for R_{mt}. Next, the daily marginal expected shortfall (MES) is given by the partial derivative of the system expected shortfall ES_{mt} with respect to the weight of entity i:

$$MES_{it} = \frac{\partial ES_{mt}}{\partial w_{it}} = -\mathbb{E}_{t-1} \big[R_{it} | R_{mt} < C \big] \tag{8}$$

Subsequently, the quarterly systemic risk measure $SRISK$ (in dollar) is given by:

$$SRISK_{it} = kD_{it} - (1-k) W_{it} (1 - LRMES_{it}) \tag{9}$$

where k is the prudential capital fraction, D_{it} is the book value of debt, W_{it} is the market value of equity, and $LRMES_{it}$ stands for long-run MES_{it}. Following Brownlees and Engle (2016), we set k to be 8%. We approximate $LRMES_{it}$ using $LRMES_{it} \simeq 1 - \exp(-18 MES_{it})$

following the suggestion of Acharya et al. (2012). The contribution of entity i to $SRISK$ is given by:

$$SRISK\%_{it} = \frac{(SRISK_{it})_+}{\sum_{i=1}^{N}(SRISK_{it})_+} \tag{10}$$

where $(x)_+$ denotes $\max(x, 0)$.

2.4. Explanatory variables

In this subsection, we present all explanatory variables used in this study.

2.4.1. Shadow indicator

To measure the impact of shadow insurance, we construct the following indicator:

$$Shadow_{it}(SI_{it}, TR_{it}) = \begin{cases} SI_{it}/TR_{it} & \text{if } SI_{it} > SI_0 \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

where SI_{it} is the amount of shadow insurance practised by entity i at time t; and TR_{it} is the total insurance reserve entity i has at time t which serves as the scaling variable.[5] A large value of $Shadow_{it}$ is an indication of high risk because it means that insurer i is heavily engaged in shadow insurance with little reserve, at time t.[6] Finally, SI_0 is set to be zero as we are interested in all the shadow insurance deals regardless of the dollar amount.

2.4.2. Size and interconnectedness

We include *size* and *interconnectedness* in the analysis as these regulatory metrics are often criticised for being the leading factors driving systemic risk. As a proxy for size, we use the log of total market equity for each entity divided by the log of the cross-sectional average of market equity following Adrian and Brunnermeier (2016).[7] The default of a large financial institution might create a domino effect leading to the failure of other entities in the financial system. Thus, we expect size to be positively related to systemic risk.[8]

To measure the interconnectedness of our sample insurers with the banking system, we use the principal component approach proposed by Billio et al. (2012). For a given quarter, we let σ_i^2 denotes the variance of entity i's daily return. We then denote Z_i as the standardised daily

[5]Note that we observe shadow insurance and total reserve on the yearly and quarterly basis, respectively. To solve the mixed frequency problem, we create quarterly SI_{it} by taking the simple average of annual shadow insurance.

[6]Replacing total reserve with total assets does not alter our conclusions.

[7]Our conclusions remain unaltered if we replace total market equity with total assets.

[8]See, e.g., Adrian and Brunnermeier (2016), Bierth et al. (2015), Huang et al. (2012) and Laeven et al. (2016).

stock returns of entity i and $V = \text{Cov}(Z_i, Z_j)$ as the covariance matrix of the standardised daily returns across a total of N financial entities.[9] Next, we decompose matrix V by means of principal component analysis to obtain eigenvalues $\lambda_1, ..., \lambda_N$, and a matrix $L = (L_{ik})_{ik}$ that contains the eigenvectors of V. The variance of the system is given by:

$$\sigma_s^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k \tag{12}$$

The univariate measure (in logarithm) of an entity's interconnectedness with the system is given by:

$$PCAS_{i,n} = \log\left(\sum_{k=1}^{n} \frac{\sigma_i^2}{\sigma_s^2} L_{ik}^2 \lambda_k \bigg|_{h_n > H} \right) \tag{13}$$

where $h_n = \sum_{k=1}^{n} \lambda_k / \sum_{k=1}^{N} \lambda_k$. Following Billio et al. (2012), H is set to be 0.33. In general, the literature agrees that a high degree of interconnectedness with the financial system increases an entity's systemic relevance. We therefore expect this variable to be positively related to systemic risk.[10]

2.4.3. Insurer-specific control variables

In addition to the main explanatory variables, we include insurer-specific features as control variables. However, some insurers do not report the control variables needed for our analysis. Specifically, 13 entities do not report *loss ratio*; 11 insurers do not report *total reserves*; 5 entities do not report *total operating expenses*; 2 insurers do not report *return on assets*; and 8 entities do not report *return on equity*. These missing series are estimated using the cross-sectional average.

To control for entity idiosyncratic risk, we use both VaR defined in (1) and *leverage*.[11] Clearly, the former is more related to $\Delta CoVaR$, whereas the latter is more relevant for $SRISK$ because $SRISK$ is a function of debt and market value of equity. Indeed, our empirical analysis shows that leverage and VaR are often redundant in the regression of $\Delta CoVaR$ and $SRISK$, respectively. Therefore, we include according VaR in the analysis of $\Delta CoVaR$ and leverage in the regression of $SRISK$ for parsimony. To proxy for leverage, we follow Acharya et al. (2017) to use the book value of assets net book value of equity plus

[9] We consider an additional of 745 banks worldwide available on *Datastream* for the computation of interconnectedness between our main sample and the banking system. This leads to a total of $N = 960$ financial entities.

[10] See, e.g., Billio et al. (2012), Cai et al. (2018), Drehmann and Tarashev (2013), Koijen and Yogo (2017) and Schwarcz (2015).

[11] We thank an anonymous referee for this suggestion.

the market value of equity, divided by the market value of equity.

We also include other insurer features previously studied by Bierth et al. (2015) as control variables. We use *debt maturity* which is computed using long-term debt divided by total debt to control for the financial health of an entity.[12] To control for insurance portfolio quality, we include the *loss ratio*. Loss ratio is computed by adding claim and loss expenses plus long term insurance reserves, divided by premiums earned. We use *market-to-book ratio* as another control variable to capture market's perception of an entity's value, calculated using the ratio between the market value of equity and book value of equity. To control for manager quality, we include *expense ratio* that is computed as the ratio of operating expenses to total book assets. We use *other income* to control for the degree to which an insurer engages in non-traditional and non-insurance activities. As a proxy for profitability of the insurance entity, we employ the conventional *return on assets* (RoA).[13]

2.5. Descriptive statistics

Given the evidence in Zhang et al. (2015) that the extent to which $\Delta CoVaR$ and $SRISK$ react to economic downturn vary, we conduct our analysis over two periods: The full sample period and a subsample that focuses on financial distress. In particular, our subsample spans from 2006Q1 to 2011Q2, covering both the United States subprime mortgage crisis and the European great depression. We begin from 2006 because there exists evidence suggesting that is when the accumulation of risk leading to the subprime financial crisis started (see, e.g., Dou et al., 2014; Garriga and Hedlund, 2020). The most notable spillover effect from this crisis is the economic depression in Europe, with Greece being one of the hardest hit countries (Ureche-Rangau and Burietz, 2013). From November 2009 to April 2010, the spread of Greek bonds over German ones increased by an astonishing 451 basis points (Arghyrou and Tsoukalas, 2011). Finally, the credit rating of Greece was downgraded by S&P to its lowest rating in 2011Q2, which marks the end of our subsample.

Table 3 summarises the quarterly variables for both sample periods. Note that a low (high) $\Delta CoVaR$ ($SRISK$) estimate is the indication of systemic risk relevance. Besides, we summarise the positive dollar term of $SRISK$ for ease of comparison with the literature. For the full sample period, the mean estimate of $\Delta CoVaR$ yields -0.14 with a maximum and a minimum of 0.16 and -1.77, respectively. We observe that the average $\Delta CoVaR$ estimate is closer to its maximum than its minimum, suggesting fat tail on the left side of the distribution. This is confirmed by a skewness estimate of -3.29, indicating that the systemic

[12] Among all observations for debt maturity, 21 are erroneous (lager than one), and we replace them with the value of one.

[13] Replacing *return on assets* with *return on equity* does not alter our conclusions.

importance of average insurers is less significant economically than certain entities, over a certain period of time. The descriptive statistics for $SRISK$ over the entire sample period yield similar pattern. The mean estimate of $SRISK$ is \$2.5 million with a positive skewness of 6.65, highlighting that on average, certain insurance entities significantly contribute more to financial instability, at certain points in time. During the period of financial distress, the mean estimates of $\Delta CoVaR$ (-0.17) and $SRISK$ (\$2.7 million) are, respectively, lower and higher than their full sample counterparts. This is expected because systemic risk measures should reflect the financial downturn, though the average $SRISK$ is relatively less sensitive to the event. Overall, the descriptive statistics of the distress period show similar pattern to those obtained under the full sample.

[Table 3 about here]

To compare the response of $\Delta CoVaR$ and $SRISK$, in Fig. 5 we plot the time evolutions for the cross-sectional means of the two systemic risk measures. Focusing on the average of all entities (solid lines), we observe that $\Delta CoVaR$ is relatively more reactive to the distress period while $SRISK$ exhibits much more resilience. For instance, $\Delta CoVaR$ displays the expected spike at the height of the subprime crisis, while the response from $SRISK$ is less profound. This is consistent with Zhang et al. (2015), who find $\Delta CoVaR$ to be the most subprime-sensitive among other measures including $SRISK$, based on a diverse group of 240 international financial institutions. We also notice that $SRISK$ is relatively more reactive to other economic events such as the UK's Brexit and China's economic slowdown in 2016. This pattern is in line with Coleman et al. (2018), who focus on a group of Canadian insurance entities. Next, we disentangle the systemic risk of shadow insurers (dashed line) from non-shadow insurers (dotted line). We observe that the dashed line is always lower (higher) than the dotted line for $\Delta CoVaR$ ($SRISK$), implying that an entity practising shadow insurance is, on average, more likely to destabilise the financial system. Interestingly, the $SRISK$ of shadow insurers is more responsive to financial distress than that of non-shadow entities, suggesting that the resilience feature of average $SRISK$ is primarily driven by those entities not participating in the shadow banking activity.

[Fig. 5 about here]

To understand the driving forces behind an entity's systemic relevance, Table 4 summarises several risk-related factors of our sample by periods of study and by whether it uses shadow insurance. For both periods, we observe that entities engaging in shadow insurance are more systemic relevant than their non-shadow counterparts with the shifts in $SRISK$ being more profound, as per Fig. 5. Besides, we notice that shadow insurers are, on average, larger and more interconnected with the financial system. They also carry higher idiosyncratic risk as shown by a lower VaR and a higher leverage. This is consistent with Benoit et al. (2013), who show that if an entity is more interconnected with the financial system and exhibits higher idiosyncratic risk, it should be more systemic relevant irrespective of which of the two systemic risk measures is used. Interestingly, the leverage of shadow insurers experiences some major upshifts during financial distress, while that of non-shadow entities encounters a weak opposite alleviation. Because $SRISK$ is closely related to leverage, this explains why, in Fig. 5, the $SRISK$ of shadow entities is relatively more responsive to financial distress than that of non-shadow insurers.

[Table 4 about here]

From the descriptive statistics reported thus far, we learn that an entity using shadow insurance is generally more systemic relevant. Without taking into account the shadow activity's magnitude — as measured by the shadow indicator in (11) — we cannot yet imply that the practice of shadow insurance has a direct impact on systemic risk of the financial system. To have an idea about the relation between shadow activity and systemic relevance, in Fig. 6 we plot the shadow indicator and systemic risk estimates of Manulife, the most active shadow entity in our sample. We observe that the shadow indicator co-moves with $\Delta CoVaR$ during financial distress. On the other hand, the co-movement with $SRISK$ appears to be stronger in the long run. Overall, the plot suggests that shadow insurance seems to drive the risk of financial system at various points in time depending on the employed systemic risk measures. This visual inspection is, of course, unconditional and specific to the case of Manulife.

[Fig. 6 about here]

3. Empirical results

In this section, we evaluate and report the factors driving an entity's contribution to systemic risk. First, we report the correlation matrix of the panel variables in Table 5. Given the negative (positive) nature of $\Delta CoVaR_{it}$ ($SRISK\%_{it}$), negative (positive) correlation implies systemic relevance. We observe a weak but statistically significant correlation between the two systemic risk measures, in line with the cross-sectional averages in Fig. 5. The shadow indicator shows the expected negative and positive pairwise relations with $\Delta CoVaR_{it}$ and $SRISK\%_{it}$, respectively. This suggests that, on average, the practice of shadow insurance poses unconditional risks to the financial system. The regulatory metrics size and interconnectedness also display the expected signs of correlation with systemic risk. Most of the control variables show statistically significant pairwise associations with the systemic risk measures. Table 6 reports the correlation matrix focusing on the distress period. We observe a strengthened absolute correlation between $\Delta CoVaR_{it}$ and $SRISK\%_{it}$, suggesting that they exhibit stronger co-movement during the period of financial distress. The key metrics shadow indicator, size and interconnectedness display the expected stronger correlations with $\Delta CoVaR_{it}$, but weaker associations with $SRISK\%_{it}$. In particular, the decrease in correlation is more profound for the shadow indicator. Given the increase in co-movement between $\Delta CoVaR_{it}$ and $SRISK\%_{it}$ during financial distress, the weaker association between the shadow variable and $SRISK\%_{it}$ can be attributed to their stronger long-run correlation, as in the case of Manulife in Fig. 6.

[Table 5 and Table 6 about here]

In what follows, we specify a panel model that allows testing for the main hypothesis of the paper that shadow insurance increases global systemic risk while properly controlling for other potential risk factors:

$$\begin{aligned} SystemicRisk_{it} = {} & \beta_0 + \beta_1\, Shadow_{it-1} + \beta_2\, Size_{it-1} \\ & + \beta_3\, Interconnectedness_{it-1} + \Omega\, Controls^{'}_{it-1} \\ & + \alpha_i + \eta_t + \epsilon_{it} \end{aligned} \tag{14}$$

where i represents each entity and t represents each quarter; $SystemicRisk_{it}$ is one of the two systemic risk measures ($\Delta CoVaR_{it}$ and $SRISK\%_{it}$) that quantifies entity i's contribution to systemic risk at time t; $Shadow_{it-1}$, $Size_{it-1}$, $Interconnectedness_{it-1}$, and $Controls_{it-1}$ denote, respectively, the shadow indicator, size, interconnectedness, and the vector of control variables of entity i at time $t-1$; α_i are entity dummies; η_t are time dummies; and ϵ_{it} is the error term. We analyse both full sample and the distress period to investigate the behaviour of our results. We use both least-squares (LS) and generalised method of moments (GMM) to estimate model (14). The former is straightforward to implement, whereas the latter mitigates concern on possible endogeneity of regressors. Specifically, the GMM estimation first-differences each variable so as to eliminate any potential bias that may arise from unobserved entity-specific effects. We perform all of the analyses with clustered standard errors at both country and time levels to ensure robustness against unobserved heterogeneity across countries as well as time dependencies.

Table 7 reports the estimates of model (14) using LS for both $\Delta CoVaR_{it}$ and $SRISK\%_{it}$ systemic risk measures. Specification (i) reports the results using $\Delta CoVaR_{it}$ measure for the full sample period. In line with the theory, we find statistically significant evidence showing an entity that is highly interconnected with the financial system contributes more to systemic risk. Besides, size shows the expected negative coefficient and is significant at the 5% level, implying that a larger entity tends to be more systemic relevant. We observe that the shadow indicator is negative and statistically significant at the 5% level. This finding suggests that the practice of shadow insurance increases systemic risk, as we hypothesised. In particular, an increase in the shadow indicator by one standard deviation leads to a decrease of 0.11% in $\Delta CoVaR_{it}$ (0.0098 $\times$ -0.1108), in the long run. Specification (ii) reports the analysis results using $\Delta CoVaR_{it}$ for the period of financial distress. Size and interconnectedness continue to play a crucial role in driving systemic risk. The shadow indicator shows the expected negative coefficient and is significant at the 1% level. It also displays a higher economic significance: An increase in the shadow indicator by one standard deviation leads to a decrease of 0.22% in $\Delta CoVaR_{it}$ (0.0094 $\times$ -0.2328). To test whether the impact of shadow insurance is stronger during distress period, in the full sample analysis we add an interaction term given by the shadow indicator and a dummy variable that takes the value of one during financial distress.[14] The results are reported in specification (iii). Indeed, we observe a negative and statistically significant coefficient for the interaction variable, suggesting that the practice of shadow insurance has a more pronounced economic effect during the distress period. Besides, the impact is so significant that the non-distress period effect diminishes, as implied by the insignificant shadow indicator.

Next, we refer to specifications (iv) and (v) in Table 7 that report the regressions of $SRISK\%_{it}$ over the full sample and the distress periods, respectively. For both estimation periods, size is positive and statistically significant, suggesting that a larger entity contributes more to systemic risk. Interconnectedness also displays the expected positive sign and is significant at the 5% level. Our shadow indicator shows the expected positive and statistically significant coefficient for the analysis of both the full sample as well as the distress period. Particularly, a unit standard deviation increment of the shadow indicator increases $SRISK\%_{it}$ by 0.20% and 0.12% for the full sample (0.0098 $\times$ 0.1999) and distress period (0.0094 $\times$ 0.1324), respectively. We test whether the shadow variable has a lower impact during the distress period in specification (vi). Interestingly, the shadow-distress interaction term displays a negative and significant coefficient, implying that shadow insurance has relatively weaker effect on systemic risk during financial distress. From the pairwise associations reported in Table 5 and Table 6, we note that the absolute correlation between $\Delta CoVaR_{it}$ and $SRISK\%_{it}$ increases during financial distress. Specifications (i)–(iii) in Table 7 further suggest that shadow insurance has a higher impact on $\Delta CoVaR_{it}$ during the period of

[14] We thank an anonymous referee for this suggestion.

distress. Therefore, the relatively weaker impact on $SRISK\%_{it}$ from the shadow variable during financial distress can be attributed to their stronger long-run association that depreciates other subsample effects. Overall, the analysis of $SRISK\%_{it}$ provides further statistical evidence that shadow insurance poses non-trivial risks to the financial system.

[Table 7 about here]

Table 8 reports the estimates of model (14) via GMM for both $\Delta CoVaR_{it}$ and $SRISK\%_{it}$ systemic risk measures. First, we follow the conventional procedure by allowing the use of all possible lagged values of each variable as instruments. Next, we rigorously reduce the number of instruments as Roodman (2009) shows via simulations the potential detrimental effects on the Hansen test given an extensive instrument collection. The author also suggests that the Hansen test should be satisfied with a high p-value to avoid the danger of false positive. In this paper, we carry out both Hansen and difference-in-Hansen tests, and the p-values of the two tests are well above the usual rejection level. The former ensures the joint validity of the selected instruments, whereas the latter assures that instrument exogeneity is satisfied. Finally, we perform the Arellano-Bond test for second-order serial correlation AR(2) to ensure the validity of our GMM results further.

Specifications (i) and (ii) in Table 8 report the analysis results using $\Delta CoVaR_{it}$ as the dependent variable for the full sample and the distress periods, respectively. For both estimation windows, we find that the regulatory systemic metrics size and interconnectedness yield the expected negative and significant coefficients; and we observe statistically significant evidence that shadow insurance poses systemic threat to the global financial sector. In particular, an increase in the shadow indicator by one standard deviation decreases $\Delta CoVaR_{it}$ by 0.26% and 0.60% for the full sample (0.0098 × -0.2686) and the distress period (0.0094 × -0.6361), respectively. In specification (iii), we observe a negative and significant coefficient for the shadow-distress interaction variable, suggesting that the impact shadow insurance has on the financial system is economically more pronounced during the period of distress.

Next, specifications (iv) and (v) report the regressions of $SRISK\%_{it}$ measure for the full sample and the distress periods, respectively. For both estimation windows, size and interconnectedness display the positive and significant coefficients as per our expectation. The coefficient of shadow is positive and statistically significant for both the analysis of the full period and the financial distress. In particular, a unit standard deviation increment of the shadow indicator increases $SRISK\%_{it}$ by 0.13% and 0.08% for the full sample (0.0098 × 0.1321) and distress period (0.0094 × 0.0817), respectively. Finally, the interaction variable in specification (vi) provides marginal evidence that shadow insurance has a more profound impact on systemic risk in the long run.

[Table 8 about here]

To sum up, the regressions of $\Delta CoVaR$ and $SRISK$ via LS provide evidence that the shadow indicator increases systemic risk in the distress period and the long run. For $\Delta CoVaR$, the effect is greater during financial distress, whereas $SRISK$ suggests a more pronounced long-run impact. The main results are further supported using GMM estimation. Overall, our analyses provide non-trivial evidence that the practice of shadow insurance affects systemic risk and confirm the central hypothesis of the paper.

4. Conclusions

In this paper, we evaluated the contribution of shadow insurance to systemic risk of the global financial sector over 2004–2017. We collected 215 international insurance entities from *Datastream* that made up our main sample. To identify shadow insurance activities, we scrutinised every reinsurance agreement from the NAIC Schedule S filings, available to us through *Market Intelligence*. We identified 29 key shadow insurers, and we found that shadow insurance had become an increasingly common practice to reduce regulatory capital with the ultimate goal to increase risk exposure. We documented about 2.8 cents every dollar ceded were shadow in 2004 with the figure growing significantly to 21 cents every dollar in 2017. We found shadow entities to be generally riskier, larger, more interconnected with the financial system and more systemic relevant than their non-shadow counterparts. Our panel analyses provided statistical evidence that the practice of shadow insurance affected financial stability, with $\Delta CoVaR$ suggested a stronger impact during distress period and $SRISK$ indicated a more profound long-run effect.

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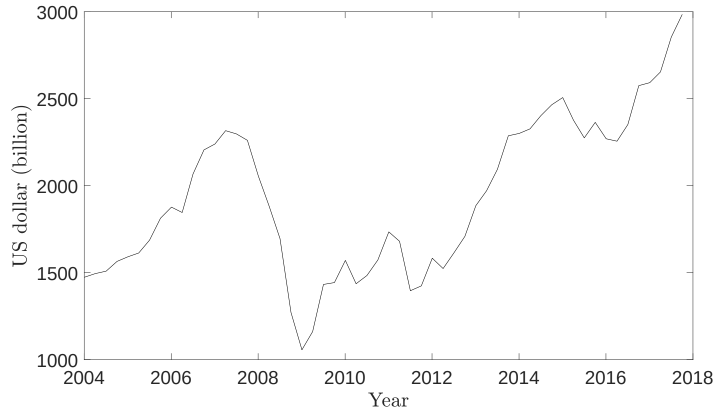


Fig. 1. Market capitalisation. The figure displays the market capitalisation of our sample of 215 insurers over the period 2004Q1–2017Q4, in billion US dollar. Data source: *Datastream*.

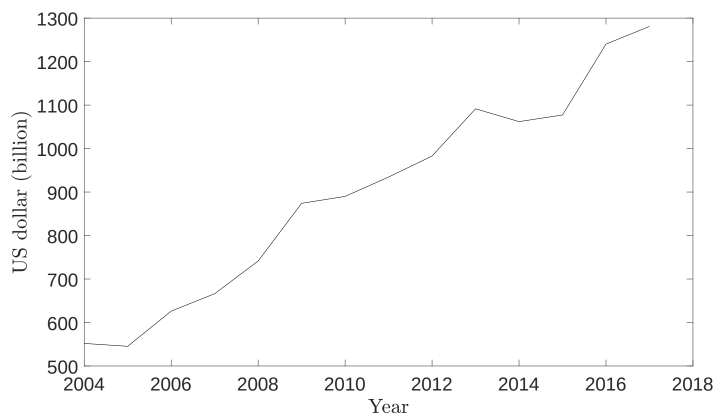


Fig. 2. Total reinsurance ceded. The figure displays the growth of the reinsurance industry over the period 2004–2017, in billion US dollar. Data source: *Market Intelligence*.

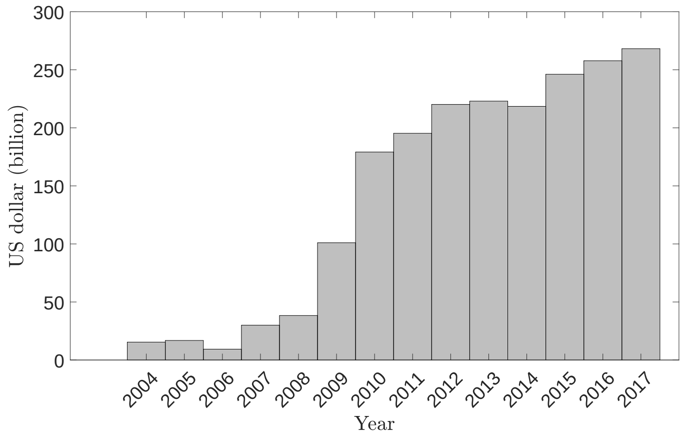


Fig. 3. Shadow insurance. The figure displays the growth of shadow insurance activity over the period 2004–2017, in billion US dollar. Data source: *Market Intelligence*.

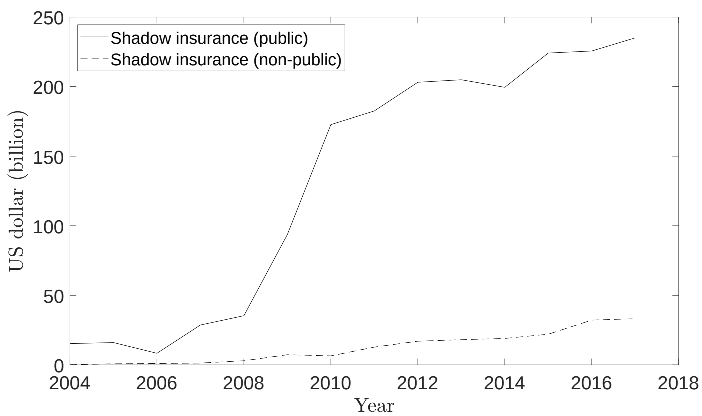
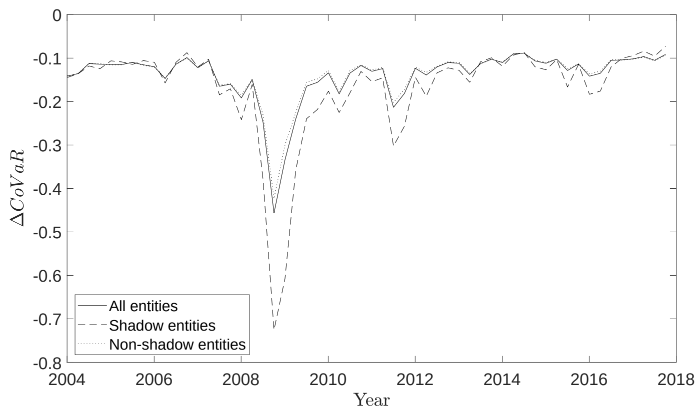
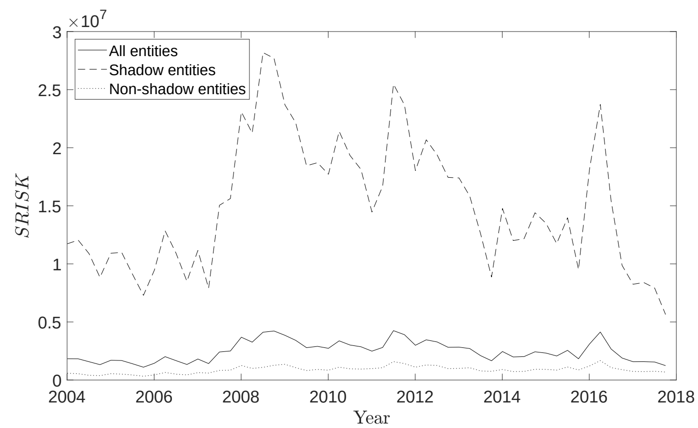


Fig. 4. Shadow insurance (public) vs shadow insurance (non-public). The figure displays the amount of shadow insurance practised by entity belonging to a public company vs non-public company over the period 2004–2017, in billion US dollar. Data source: *Market Intelligence*.

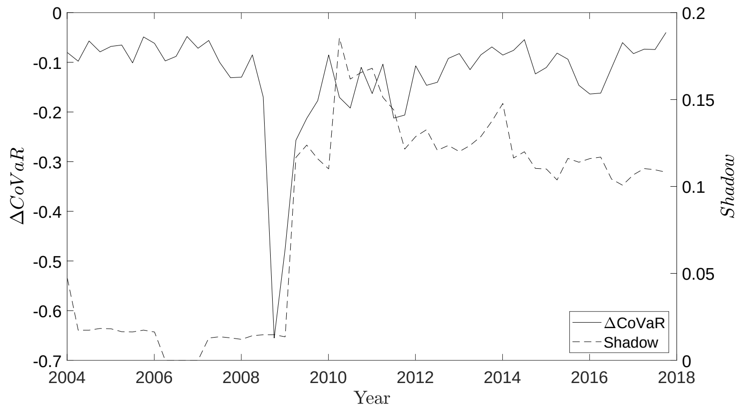


(a) $\Delta CoVaR$

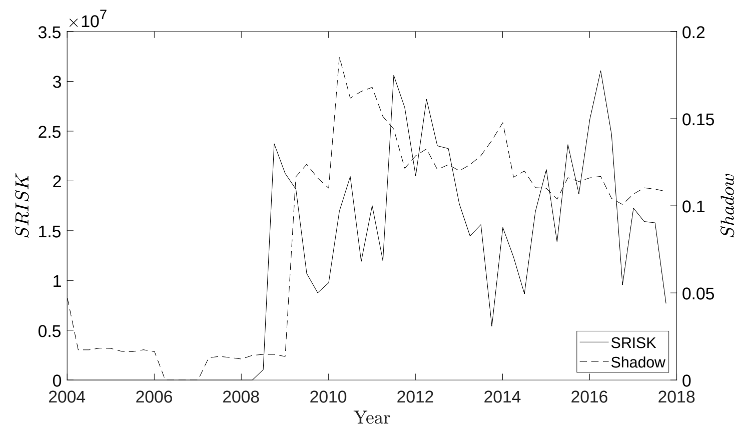


(b) $SRISK$

Fig. 5. Time evolution of systemic risk. The figures plot the mean quarterly systemic risk measures $\Delta CoVaR$ and $SRISK$ of all insurers (solid line), shadow insurers (dashed line) and non-shadow insurers (dotted line), over the full sample period 2004Q1–2017Q4. The positive dollar term of $SRISK$ is used.



(a) Manulife: $\Delta CoVaR$ and $Shadow$



(b) Manulife: $SRISK$ and $Shadow$

Fig. 6. Systemic risk and shadow indicator series of Manulife. The figures plot the quarterly shadow indicator (dashed line) and systemic risk measures $\Delta CoVaR$ and $SRISK$ (solid lines) of Manulife over the full sample period 2004Q1–2017Q4. The positive dollar term of $SRISK$ is used.

Table 1. Sample composition

Country	# Entities	Country	# Entities
Australia	4	Kenya	1
Austria	2	Korea, Republic of	7
Belgium	1	Malaysia	6
Bermuda	8	Malta	1
Brazil	1	Mexico	2
Canada	10	Morocco	2
Chile	2	Netherlands	2
Cyprus	2	New Zealand	1
Denmark	2	Norway	1
Egypt	1	Pakistan	8
Finland	1	Singapore	4
France	5	South Africa	5
Germany	9	Spain	2
Greece	1	Sri Lanka	3
Hong Kong	2	Switzerland	7
India	3	Taiwan, Province of China	9
Ireland	1	Thailand	8
Israel	8	Turkey	5
Italy	6	United Kingdom	9
Japan	2	United States	61

NOTES: The table reports the number of insurance entities by country in our international sample. Data source: *Datastream*.

Table 2. Shadow insurers

Shadow insurer	Country	Shadow insurance	Shadow index
AEGON N.V.	Netherlands	68,287.88	499.647
Allianz Group	Germany	1,748.39	3.125
American International Group, Inc.	United States	68,460.47	204.889
AXA	France	100,183.64	184.810
Brighthouse Financial, Inc.	United States	2,109.62	-
Centene Corporation	United States	13.64	10.056
Chubb Limited	Switzerland	6.73	0.133
Cigna Corporation	United States	0.45	0.018
Dai-ichi Life Holdings, Inc.	Japan	8,590.69	-
FGL Holdings	United States	7,720.02	-
Genworth Financial, Inc.	United States	13,994.92	-
Legal & General Group Plc	United Kingdom	15,154.48	60.311
Lincoln National Corporation	United States	63,208.69	766.231
Manulife Financial Corporation	Canada	831,154.11	5262.104
MetLife, Inc.	United States	238,144.41	700.263
National General Holdings Corporation	United States	0.01	-
Primerica, Inc.	United States	26,166.18	-
Prudential Financial, Inc.	United States	13,306.91	48.574
Prudential Plc	United Kingdom	0.49	0.001
Reinsurance Group of America, Incorporated	United States	15,500.06	1076.965
SCOR SE	France	113.08	4.341
Security National Financial Corporation	United States	0.11	0.276
Sun Life Financial Inc.	Canada	30,496.34	368.483
Swiss Re AG	Switzerland	37,335.80	279.541
Tokio Marine Holdings, Inc.	Japan	23.23	0.181
Torchmark Corporation	United States	33,341.90	3276.872
Unum Group	United States	181,380.69	4153.791
Voya Financial, Inc.	United States	64,801.15	-
Zurich Insurance Group AG	Switzerland	23,667.59	126.654

NOTES: The table displays the names of shadow insurers and the corresponding countries they are located. Besides, the table reports the amount of shadow insurance practised (in million US dollar), aggregated over 2004–2017. The shadow index is the ratio of total shadow insurance to the average quarterly reserve held. We do not report the shadow index of some entities as these entities are subsequently dropped in the analysis due to data availability. Data source: *Market Intelligence*.

Table 3. Descriptive statistics

	Mean	Std. dev.	Min	Max	Skew.	Kur.
Full period (2004Q1–2017Q4)						
$\Delta CoVaR$	-0.1400	0.1139	-1.7713	0.1637	-3.2869	24.9535
$SRISK$ (in billions)	0.0025	0.0098	0.0000	0.1619	6.6536	62.2597
$Shadow$	0.0014	0.0098	0.0000	0.1855	9.9587	116.4354
$Size$	0.9111	0.1018	0.5558	1.1528	-0.1726	2.2689
$Interconnectedness$	-10.5645	1.2537	-18.7689	-4.7360	-0.8222	5.9034
VaR	-0.2832	0.2144	-4.0539	0.0000	-3.9369	34.1056
$Leverage$	8.3289	10.5084	1.0066	298.0079	7.4118	128.9634
$Debt\ maturity$	0.7885	0.3400	0.0000	1.0000	-1.5208	3.7719
$Loss\ ratio$	159.0058	1869.8982	-1097.2800	79649.2800	34.7699	1313.3755
$Market\ to\ book$	1.6024	1.2586	-5.9023	22.5108	3.4185	25.0726
$Operating\ expenses$	2.2513	113.7546	-0.5462	9027.2415	76.4974	5914.9003
$Other\ income$	0.0155	1.4927	-0.4524	162.0860	106.6433	11550.5592
RoA	2.5750	16.8849	-919.1300	1056.2500	24.6892	3060.3365
Distress period (2006Q1–2011Q2)						
$\Delta CoVaR$	-0.1725	0.1473	-1.7713	0.1564	-3.0127	18.6358
$SRISK$ (in billions)	0.0027	0.0113	0.0000	0.1619	6.7317	60.2114
$Shadow$	0.0011	0.0094	0.0000	0.1855	11.5949	158.9202
$Size$	0.9113	0.1022	0.6587	1.1497	-0.1639	2.2449
$Interconnectedness$	-10.6507	1.3150	-18.7689	-5.5103	-1.1110	6.2675
VaR	-0.3463	0.2591	-4.0539	0.0000	-3.2934	24.5015
$Leverage$	8.2505	12.4927	1.0232	298.0079	9.5724	157.1713
$Debt\ maturity$	0.7867	0.3440	0.0000	1.0000	-1.5130	3.7186
$Loss\ ratio$	89.1225	123.9234	-1097.2800	1928.9600	7.6980	110.5074
$Market\ to\ book$	1.6673	1.2767	-0.7595	13.1590	2.9601	16.5473
$Operating\ expenses$	1.1155	15.3583	-0.2476	357.5246	15.9248	268.4476
$Other\ income$	0.0340	2.3570	-0.3863	162.0860	68.7305	4725.9244
RoA	2.6214	6.9056	-55.9100	111.7700	6.7756	113.9995

NOTES: The table reports descriptive statistics of the systemic risk measures $\Delta CoVaR$ and $SRISK$ estimated at quarterly frequency for a sample of 215 insurance entities worldwide. The positive dollar term of $SRISK$ is used. Besides, the tables reports descriptive statistics for the set of quarterly independent variables. We report the mean, standard deviation, minimum, maximum, skewness and kurtosis. Data source: *Datastream* and *Market Intelligence*.

Table 4. Descriptive statistics: Shadow and non-shadow insurers

	Shadow insurers				Non-shadow insurers			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Full period (2004Q1–2017Q4)								
$\Delta CoVaR$	-0.1685	0.1428	-1.3786	-0.0225	-0.1364	0.1092	-1.7713	0.1637
$SRISK$ (in billions)	0.0151	0.0234	0.0000	0.1619	0.0009	0.0041	0.0000	0.0846
$Shadow$	0.0122	0.0269	0.0000	0.1855	0.0000	0.0000	0.0000	0.0000
$Size$	1.0237	0.0682	0.7363	1.1470	0.8969	0.0963	0.5558	1.1528
$Interconnectedness$	-10.0184	0.7847	-13.0931	-7.3624	-10.6331	1.2844	-18.7689	-4.7360
VaR	-0.2861	0.2532	-3.2678	-0.0446	-0.2828	0.2091	-4.0539	0.0000
$Leverage$	15.0538	19.5413	1.1787	298.0079	7.4838	8.3638	1.0066	128.9460
Distress period (2006Q1–2011Q2)								
$\Delta CoVaR$	-0.2266	0.1980	-1.3786	-0.0225	-0.1657	0.1382	-1.7713	0.1564
$SRISK$ (in billions)	0.0174	0.0271	0.0000	0.1619	0.0009	0.0045	0.0000	0.0846
$Shadow$	0.0101	0.0265	0.0000	0.1855	0.0000	0.0000	0.0000	0.0000
$Size$	1.0219	0.0718	0.7427	1.1332	0.8974	0.0968	0.6587	1.1497
$Interconnectedness$	-10.0235	0.7950	-13.0931	-7.3624	-10.7295	1.3460	-18.7689	-5.5103
VaR	-0.3889	0.3499	-3.2678	-0.0561	-0.3410	0.2449	-4.0539	0.0000
$Leverage$	17.5090	28.3108	1.2780	298.0079	7.0871	7.9378	1.0232	108.5136

NOTES: The table reports descriptive statistics of the systemic risk measures $\Delta CoVaR$ and $SRISK$ estimated at quarterly frequency for shadow and non-shadow insurers. The positive dollar term of $SRISK$ is used. Besides, the tables reports descriptive statistics for selected independent variables. We report the mean, standard deviation, minimum and maximum. Data source: *Datastream* and *Market Intelligence*.

Table 5. Correlation matrix: Full period

	$\Delta CoVaR_{it}$	$SRISK\%_{it}$	$Shadow_{it}$	$Size_{it}$	$Interconnect-edness_{it}$	VaR_{it}	$Leverage_{it}$
$\Delta CoVaR_{it}$	1						
$SRISK\%_{it}$	-0.0569***	1					
$Shadow_{it}$	-0.0368***	0.0841***	1				
$Size_{it}$	-0.1259***	0.3423***	0.1353***	1			
$Interconnectedness_{it}$	-0.1187***	0.1928***	0.0531***	0.1355***	1		
VaR_{it}	0.6284***	-0.0345***	0.0215**	0.2268***	-0.2166***	1	
$Leverage_{it}$	-0.1269***	0.4470***	0.0347***	0.1125***	0.1725***	-0.1602***	1
$Debt\ maturity_{it}$	-0.0708***	-0.0350***	0.0540***	0.3310***	0.0432***	0.0735***	0.1172***
$Loss\ ratio_{it}$	-0.0042	0.0022	-0.0045	0.0216**	0.0193*	0.0144	0.0235**
$Market\ to\ book_{it}$	0.0323***	-0.0864***	-0.0588***	0.0559***	-0.0088	0.0690***	-0.2626***
$Operating\ expenses_{it}$	-0.0220**	-0.0125	-0.007	-0.0721***	0.0530***	-0.0835***	-0.0190*
$Other\ income_{it}$	0.0108	-0.0032	-0.0033	-0.0177*	0.0109	-0.0002	-0.0139
RoA_{it}	0.0584***	-0.1064***	-0.0281***	-0.0196*	-0.1213***	0.1421***	-0.2295***
	$Debt\ maturity_{it}$	$Loss\ ratio_{it}$	$Market\ to\ book_{it}$	$Operating\ expenses_{it}$	$Other\ income_{it}$	RoA_{it}	
$Debt\ maturity_{it}$	1						
$Loss\ ratio_{it}$	0.0233**	1					
$Market\ to\ book_{it}$	-0.1608***	0.0875***	1				
$Operating\ expenses_{it}$	-0.0535***	0.0002	-0.0550***	1			
$Other\ income_{it}$	0.0195*	0.001	0.0260**	0.1086***	1		
RoA_{it}	-0.0758***	-0.0172*	0.2116***	-0.2344***	-0.0348***	1	

NOTES: The table reports the pairwise correlation of all variables for the full period 2004Q1–2017Q4. ***, ** and * represents the significance level at 1%, 5% and 10%, respectively. Data source: *Datastream* and *Market Intelligence*.

Table 6. Correlation matrix: Distress period

	$\Delta CoVaR_{it}$	$SRISK\%_{it}$	$Shadow_{it}$	$Size_{it}$	$Interconnect-edness_{it}$	VaR_{it}	$Leverage_{it}$
$\Delta CoVaR_{it}$	1						
$SRISK\%_{it}$	-0.0784***	1					
$Shadow_{it}$	-0.0702***	0.0333**	1				
$Size_{it}$	-0.2055***	0.3384***	0.1201***	1			
$Interconnectedness_{it}$	-0.1471***	0.1789***	0.0573***	0.2453***	1		
VaR_{it}	0.6252***	-0.0619***	-0.0038	0.1373***	-0.2105***	1	
$Leverage_{it}$	-0.1489***	0.4438***	0.0169	0.1706***	0.1844***	-0.1761***	1
$Debt\ maturity_{it}$	-0.0887***	-0.0498***	0.0450***	0.3343***	0.1018***	0.0304*	0.0906***
$Loss\ ratio_{it}$	-0.0141	0.0665***	0.0173	0.1030***	0.0969***	0.0253*	0.1224***
$Market\ to\ book_{it}$	0.0714***	-0.0612***	-0.0443***	0.0979***	0.0363**	0.0650***	-0.2150***
$Operating\ expenses_{it}$	0.0164	-0.017	-0.0084	-0.1138***	0.0135	-0.0523***	-0.0385***
$Other\ income_{it}$	0.0174	-0.0035	-0.0018	-0.0351**	-0.0698***	0.0196	-0.0006
RoA_{it}	0.0436***	-0.0770***	-0.0181	-0.0464***	-0.0984***	0.1376***	-0.1642***

	$Debt\ maturity_{it}$	$Loss\ ratio_{it}$	$Market\ to\ book_{it}$	$Operating\ expenses_{it}$	$Other\ income_{it}$	RoA_{it}
$Debt\ maturity_{it}$	1					
$Loss\ ratio_{it}$	0.0706***	1				
$Market\ to\ book_{it}$	-0.1913***	0.0147	1			
$Operating\ expenses_{it}$	0.0157	0.0002	0.0534***	1		
$Other\ income_{it}$	0.0456***	-0.0018	-0.0148	-0.0005	1	
RoA_{it}	-0.1086***	-0.0700***	0.0936***	-0.1325***	-0.0093	1

NOTES: The table reports the pairwise correlation of all variables for the distress period 2006Q1–2011Q2. ***, ** and * represents the significance level at 1%, 5% and 10%, respectively. Data source: *Datastream* and *Market Intelligence*.

Table 7. Regression results: LS estimation

	$\Delta CoVaR_{it}$ Full (i)	$\Delta CoVaR_{it}$ Distress (ii)	$\Delta CoVaR_{it}$ Full (iii)	$SRISK\%_{it}$ Full (iv)	$SRISK\%_{it}$ Distress (v)	$SRISK\%_{it}$ Full (vi)
$Shadow_{it-1}$	-0.1108**	-0.2328***	0.1032	0.1999***	0.1324***	0.2288***
	(0.0466)	(0.0894)	(0.0842)	(0.0199)	(0.0206)	(0.0199)
$Size_{it-1}$	-0.0965**	-0.1769**	-0.0916**	0.0868***	0.1127***	0.0874***
	(0.0451)	(0.0860)	(0.0450)	(0.0105)	(0.0249)	(0.0105)
$Interconnectedness_{it-1}$	-0.0063***	-0.0108***	-0.0063***	0.0002**	0.0003**	0.0002**
	(0.0017)	(0.0035)	(0.0017)	(0.0001)	(0.0002)	(0.0001)
VaR_{it-1}	0.3523***	0.3731***	0.3518***			
	(0.0106)	(0.0150)	(0.0107)			
$Leverage_{it-1}$				0.0005***	0.0003***	0.0005***
				(0.0000)	(0.0001)	(0.0000)
$Debt\ maturity_{it-1}$	0.0047**	0.0133***	0.0047**	-0.0065***	-0.0061***	-0.0065***
	(0.0021)	(0.0050)	(0.0021)	(0.0010)	(0.0014)	(0.0010)
$Loss\ ratio_{it-1}$	0.0000	0.0000**	0.0000	0.0000***	0.0000	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Market\ to\ book_{it-1}$	0.0020**	0.0033*	0.0020**	-0.0006***	-0.0009***	-0.0006***
	(0.0008)	(0.0019)	(0.0008)	(0.0001)	(0.0002)	(0.0001)
$Operating\ expenses_{it-1}$	0.0003	-0.0529***	0.0003	-0.0000	-0.0013	-0.0000
	(0.0003)	(0.0175)	(0.0003)	(0.0000)	(0.0010)	(0.0000)
$Other\ income_{it-1}$	0.0132	0.0756	0.0133	0.0016	-0.0002	0.0016
	(0.0147)	(0.0472)	(0.0146)	(0.0011)	(0.0024)	(0.0011)
RoA_{it-1}	-0.0002	-0.0001	-0.0002	-0.0001***	-0.0001***	-0.0001***
	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
$Shadow_{it-1}$			-0.5206***			-0.0704***
$\times \mathbb{1}(Distress)$			(0.2003)			(0.0125)
# Observations	9,319	3,642	9,319	9,319	3,642	9,319
# Entities	215	215	215	215	215	215
Adjusted R^2	0.8262	0.8298	0.8268	0.8032	0.8763	0.8036

Notes: The table reports the estimates of panel model regressions of quarterly $\Delta CoVaR$ and $SRISK\%$ systemic risk measures for a sample of international insurance entities on shadow indicator and various control variables using LS. The model is given by:

$$SystemicRisk_{it} = \beta_0 + \beta_1\, Shadow_{it-1} + \beta_2\, Size_{it-1} + \beta_3\, Interconnectedness_{it-1} + \Omega\, Controls_{it-1}^{'} + \alpha_i + \eta_t + \epsilon_{it}$$

where i represents each entity and t represents each time period; $SystemicRisk_{it}$ is one of the two systemic risk measures ($\Delta CoVaR_{it}$ and $SRISK\%_{it}$) that quantify the contribution of entity i to systemic risk at time t; $Shadow_{it-1}$, $Size_{it-1}$, $Interconnectedness_{it-1}$, and $Controls_{it-1}$ are, respectively, shadow indicator, size, interconnectedness, and the vector of control variables for entity i at time $t-1$; α_i are entity dummies; η_t are time dummies; and ϵ_{it} is the error term. The full sample period runs from 2004Q1 to 2017Q4, whereas the distress period runs from 2006Q1 to 2011Q2. $\mathbb{1}(Distress)$ is a dummy variable that takes the value of one during the distress period. Standard errors (reported in parentheses) are clustered by country and time. ***, ** and * represents the significance level at 1%, 5% and 10%, respectively. Data source: *Datastream* and *Market Intelligence*.

Table 8. Regression results: GMM estimation

	$\Delta CoVaR_{it}$ Full (i)	$\Delta CoVaR_{it}$ Distress (ii)	$\Delta CoVaR_{it}$ Full (iii)	$SRISK\%_{it}$ Full (iv)	$SRISK\%_{it}$ Distress (v)	$SRISK\%_{it}$ Full (vi)
$Shadow_{it-1}$	-0.2686***	-0.6361***	-0.0015	0.1321***	0.0817***	0.1613***
	(0.0913)	(0.2269)	(0.0982)	(0.0508)	(0.0298)	(0.0387)
$Size_{it-1}$	-0.2755***	-0.4230***	-0.2517***	0.0483***	0.0336***	0.0552***
	(0.0455)	(0.1395)	(0.0375)	(0.0143)	(0.0120)	(0.0111)
$Interconnectedness_{it-1}$	-0.0248***	-0.0374***	-0.0243***	0.0021***	0.0022***	0.0025***
	(0.0054)	(0.0115)	(0.0049)	(0.0008)	(0.0006)	(0.0008)
VaR_{it-1}	0.3080***	0.3067***	0.2974***			
	(0.0354)	(0.0517)	(0.0303)			
$Leverage_{it-1}$				0.0007***	0.0013***	0.0006***
				(0.0002)	(0.0002)	(0.0002)
$Debt\ maturity_{it-1}$	-0.0416**	-0.0678*	-0.0471***	-0.0084**	-0.0131***	-0.0077**
	(0.0168)	(0.0355)	(0.0159)	(0.0037)	(0.0041)	(0.0036)
$Loss\ ratio_{it-1}$	-0.0000	0.0006	-0.0000*	0.0000	-0.0000*	0.0000
	(0.0000)	(0.0008)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Market\ to\ book_{it-1}$	0.0421***	0.0234*	0.0385***	-0.0033*	0.0033	-0.0024*
	(0.0140)	(0.0141)	(0.0121)	(0.0017)	(0.0028)	(0.0014)
$Operating\ expenses_{it-1}$	-0.0201***	0.0646	-0.0193***	0.0432	0.0325	0.0446
	(0.0070)	(0.1216)	(0.0065)	(0.0327)	(0.0332)	(0.0298)
$Other\ income_{it-1}$	-0.4504	0.4478	-0.1678	-1.1212	-0.0356	-1.3696
	(1.0267)	(1.5413)	(0.9506)	(0.8913)	(0.0317)	(0.9212)
RoA_{it-1}	-0.0467***	-0.0415*	-0.0433***	-0.0006*	-0.0014	-0.0004*
	(0.0158)	(0.0238)	(0.0135)	(0.0003)	(0.0015)	(0.0002)
$Shadow_{it-1}$			-0.7877***			-0.1240*
$\times \mathbb{1}(Distress)$			(0.2854)			(0.0721)
# Observations	8,889	3,524	8,889	8,790	3,480	8,790
# Entities	215	215	215	215	215	215
# Instruments	151	75	154	152	74	154
AR(2) test	0.245	0.443	0.247	0.570	0.537	0.337
Hansen test	0.422	0.400	0.352	0.753	0.378	0.632
Diff-in-Hansen test	0.995	0.947	0.997	0.991	0.858	0.909

NOTES: The table reports the estimates of panel model regressions of quarterly $\Delta CoVaR$ and $SRISK\%$ systemic risk measures for a sample of international insurance entities on shadow indicator and various control variables using GMM. The model is given by:

$$SystemicRisk_{it} = \beta_0 + \beta_1\, Shadow_{it-1} + \beta_2\, Size_{it-1} + \beta_3\, Interconnectedness_{it-1} + \Omega\, Controls^{'}_{it-1} + \alpha_i + \eta_t + \epsilon_{it}$$

where i represents each entity and t represents each time period; $SystemicRisk_{it}$ is one of the two systemic risk measures ($\Delta CoVaR_{it}$ and $SRISK\%_{it}$) that quantify the contribution of entity i to systemic risk at time t; $Shadow_{it-1}$, $Size_{it-1}$, $Interconnectedness_{it-1}$, and $Controls_{it-1}$ are, respectively, shadow indicator, size, interconnectedness, and the vector of control variables for entity i at time $t-1$; α_i are entity dummies; η_t are time dummies; and ϵ_{it} is the error term. The full sample period runs from 2004Q1 to 2017Q4, whereas the distress period runs from 2006Q1 to 2011Q2. $\mathbb{1}(Distress)$ is a dummy variable that takes the value of one during the distress period. Standard errors (reported in parentheses) are clustered by country and time. ***, ** and * represents the significance level at 1%, 5% and 10%, respectively. Data source: *Datastream* and *Market Intelligence*.