Assessing Systemic Risk of the European Insurance Industry

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Abstract

This paper investigates the systemic relevance of the insurance industry. We do it by analysing the systemic contribution of the insurance industry vis-á-vis other industries by applying three measures, namely the linear Granger causality test, conditional value at risk and marginal expected shortfall, to three groups, namely banks, insurers and non-financial companies listed in Europe over the last 14 years. Our evidence suggests that the insurance industry shows i) a persistent systemic relevance over time, ii) it plays a subordinate role in causing systemic risk compared to banks. In addition, iii) we do not find clear evidence on the higher systemic relevance of SIFI insurers compared to non-SIFIs.

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1. Introduction

Following the 2007-2009 financial crises and the 2010-2012 European sovereign debt crises, the interest around systemic risk has become increasingly relevant.[31] After the collapse of Lehman Brothers in particular, the debate on systemic risk has been primarily focused on banks. However, recent empirical evidence suggests that institutions not traditionally associated with systemic risk, such as insurance companies, also play a prominent role in posing it. In particular, some authors find that the insurance industry has become a non-negligible source of systemic risk (e.g. Billio et al. (2012) and Weiß and Mühlnickel (2014)). This is partially in contrast to other authors, who do not find evidence of systemic relevance for the industry as a whole (e.g. Harrington (2009), Bell and Keller (2009) and the Geneva Association

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[31] Throughout this paper, we rely on the definition of systemic risk given by The Group of Ten (2001): Systemic risk is the risk that an event will trigger a loss of economic value or confidence in a substantial segment of the financial system that is serious enough to have significant adverse effects on the real economy with high probability.

(2010)). Finally, other authors take a more granular perspective and argue that insurance companies might be systemically relevant, but that such risk stems from non-traditional (banking-related) activities (Baluch et al. (2011) and Cummins and Weiss (2014)) and that in general, the systemic relevance of the insurance industry as a whole is still subordinated with respect to the banking industry (Chen et al. (2013)).

As the current literature does not provide a common understanding and clear evidence regarding the systemic relevance of the insurance industry, we aim with this paper to fill this gap by empirically investigating its systemic relevance vis-á-vis other industries.

To do so, we test three equity return-based measures of systemic risk, namely 1) the indexes based on linear Granger causality tests proposed by Billio et al. (2012) (Granger test), 2) the Conditional Value at Risk proposed by Adrian and Brunnermeier (2011) (CoVaR) and 3) the Dynamic Marginal Expected Shortfall proposed by Brownlees and Engle (2012) (DMES), on 3 groups: banks, insurers and non-financial companies, all listed in Europe. We test the systemic relevance of each institution with respect to the total system intended as the sum of the companies included in the 3 groups. Based on these estimations, we rank financial institutions according to their average systemic risk contribution over time and create an industry composition index.

Our evidence suggests that the insurance industry tends i) to persistently pose systemic risk over time and ii) to play a subordinate role with respect to the banking industry with some distinction in specific periods when the insurance industry becomes more systemic than the banking industry.

The paper is organized as follows: section 2 provides a comprehensive literature review, section 3 describes the methodology, section 4 the data; section 5 describes the results and section 6 concludes the analysis.

2. Literature review

The literature on systemic risk has been steadily growing following the crises. In particular, a wide range of new methodologies for testing the systemic contribution of financial institutions has been proposed. Moreover, both academia and regulators have dedicated more attention to the role of non-banking financial institutions: among

these institutions, insurance companies emerged as a potential source of systemic risk.[32]

Before the crisis, there was substantial agreement among scholars in considering the insurance industry to be not systemically relevant. However, in the literature that emerged in the aftermath of the crisis, although many studies still consider the insurance industry non-systemically relevant as a whole, a clear-cut indication does not emerge anymore.

As a matter of fact, looking at the evidences stemming from market based data that rely on the assumption that prices reflect all the necessary information[33], substantial differences in the evaluation of the insurance industry emerge. For instance, Acharya et al. (2010) argue that insurance companies are overall the least systemically relevant financial institutions. The authors provide estimations of the spillover effects through a measure of conditional capital shortfall, i.e. Systemic Expected Shortfall (SES) and Marginal Expected Shortfall (MES) for the US financial industry during the 2007-2009 crises. The contribution of Adrian and Brunnermeier (2011) extends the traditional value at risk concept to the entire financial system conditional on institutions being in distress (ΔCoVaR). The authors apply the measure to a set of institutions, including banks and thrifts, investment banks, government sponsored enterprises and insurance companies and find no distinction between the systemic relevance of different types of institutions. By contrast, Billio et al. (2012) apply the linear and non-linear Granger causality test to a sample of banks, insurers, hedge funds and broker dealers operating in the U.S. in order to establish pairwise Granger causality among equity returns of financial institutions. Their evidence suggests that during the 2008 financial crisis, besides banks, insurance companies were a major source of systemic risk. This conclusion is partially in contrast to Chen et al. (2013): the authors agree that the linear Granger causality test attributes to insurance companies a systemic relevance comparable with the systemic relevance of banks. However, they argue that when applying a linear and non-linear Granger causality test to the same series corrected for heteroscedasticity, banks tend to cause more systemic risk and for longer periods of time then insurance companies.

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[32] A comprehensive review of the literature on systemic risk in the insurance industry is provided by Eling and Pankoke (2012).

[33] A comprehensive review of the models applied to systemic risk is provided by Bisias et al. (2012).

Both theoretical and empirical research that take into consideration fundamentals of the insurance industry provide ambiguous indications about the systemic relevance of insurers. Even though the common understanding classifies the insurance industry as not systemically relevant, distinctions mainly driven by the engagement in specific business lines emerge.

The Geneva Association (2010) conducts an analysis on the role played by insurers during the 2008 crisis and argues that the substantial differences between banks and insurance companies, namely the long-term liability structure of insurers compared to banks and the strong cash flow granted by the inversion of the cycle, is sufficient to rule out any systemically implications of the insurance industry during the financial crises aside from the companies highly exposed towards non-core insurance activities.

The higher systemic relevance of non-traditional versus traditional insurance activities is analysed by other authors such as Bell and Keller (2009) who investigate the relevant risk factors stemming from an insurance company, or Cummins and Weiss (2014) who analyse primary indicators and contributing factors. More specifically, Cummins and Weiss (2014) add a further distinction to the dichotomy between traditional and non-traditional activities, namely the higher systemic relevance of traditional life compared to the P&C business: this is mainly driven by the higher leverage, interconnectedness and exposure to credit, market and liquidity risk. Similar conclusions are reached by Baluch et al. (2011), who find that the fundamental reason behind the systemic relevance of the bank-like business type is due to the massive amount of interconnectedness, and by Harrington (2009) who concludes that systemic risk is potentially higher for life insurers due to the higher leverage, sensitivity to asset value decline and potential policyholder withdrawals during a financial crisis.

An additional strand of research based both on market and accounting data tend to confirm the difficulties in defining the insurance industry as systemically relevant. Weiß and Mühlnickel (2014) estimate the systemic risk contribution based on CoVaR and MES for a sample of US Insurers during the 2007-2008 crisis, inferring that insurers that were most exposed to systemic risk were on average larger, relied more heavily on non-policy holder liabilities and had higher ratios of investment income to net revenues. Weiss et al. (2014) analyse a much broader sample of insurers over a longer time horizon and find that the systemic risk contribution of the insurance sector is relatively small. However, they also argue that the contribution of insurers to systemic risk peaked during the 2007-2008 financial crisis and find that the

interconnectedness of large insurers with the insurance industry is a significant driver of the insurers' exposure to systemic risk. Finally, they argue that the contribution of insurers to systemic risk appears to be primarily driven by leverage, loss ratios and funding fragility.

It is also worth noting that an ambiguous position is attributed to reinsurance companies: studies by Swiss Re (2003) and by The Group of Thirty (2006) exclude any systemic relevance for the reinsurance business. However Cummins and Weiss (2014) claim that, despite historical evidence, both life and P&C insurers are indeed exposed to reinsurance crises. In conclusion, the existing literature provides a diversified and controversial picture of the systemic relevance of the insurance industry. On the one hand, some studies argue that due to its nature, the insurance industry does not pose systemic risk; on the other hand, some studies provide evidence on the role of the insurance industry in posing systemic risk and its growing importance in recent years, particularly driven by the engagement of insurers in non-traditional activities. Moreover the position of reinsurers appears unclear.

This paper, shed further light on the systemic relevance of the European insurance industry compared to other industries, namely banks and non-financial institution. Moreover, we aim at assessing the contribution to the riskiness of the whole system of the systemically important vis-á-vis non-systemically important insurance companies.

3. Methodology

In order to compare the systemic relevance of the insurance industry with the systemic relevance of other industries we define three groups, namely banks, insurers and non-financials and apply to them three widely used equity-based measures of systemic risk: 1) the Granger causality test proposed by Billio et al. (2012), 2) the ΔCoVaR proposed by Adrian and Brunnermeier (2011) and 3) the DMES proposed by Brownlees and Engle (2012).[34]

The literature proposes several equity-based models to assess the systemic relevance of institutions, anyhow no consensus among academia has been found on the best approach. We thus opted for the mentioned three due to i) their diffusion (many central banks and regulators apply these models), ii) their robustness (the models have been thoroughly discussed and challenged both in academia and industry, and

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[34] An extensive mathematical treatment of the three measures is provided in Appendix A.1.

finally iii) our willing to approach the measurement of the systemic relevance of an industry by different perspectives.

The three systemic risk measures tend to capture different phenomena and therefore need to be correctly interpreted. The Granger causality test is a measure that allows us to quantify the degree of connectedness of an institution vis-á-vis a system of institutions. By creating a network of pairwise statistical relations, we do not only observe the amount of interdependence, but also the direction thereof. The measure is thus a good proxy for an analysis at an aggregate level (for example industry or other clusters), but its estimation could become cumbersome when the objective is to test the individual interconnection with respect to a system of institutions as proxy for the market.[35]

The ΔCoVaR measures the difference between the CoVaR conditional on the distress of an institution, i.e. the value-at-risk of the system conditional on an institution being in distress, and the CoVaR conditional on the normal state of the institution. It is therefore able to capture the marginal contribution of a particular institution to the overall systemic risk. Finally, the DMES measures, in a dynamic setting, the expected drop in equity value of an institution when the system is in distress. It is worth mentioning that this is not a direct measure of systemic risk, but is highly related to it. The contribution of Brownlees and Engle (2012) originates from the proposal of Acharya et al. (2010), in which the marginal expected shortfall of an institution is coupled with its leverage to originate the Systemic Expected Shortfall (SES). SES measures the expected capital shortage of an individual firm conditional on a substantial reduction in the capitalization of the system. Brownlees and Engle propose a similar measure called SRISK, which is based on a dynamic estimation of the Marginal Expected Shortfall (MES) and leverage ratios. A major advantage of such a contribution is its ability to capture time-varying effects, effects which are not observable in the framework of Acharya et al. (2010). However, both measures rely on the estimation of the MES and of pre-determined leverage ratios: in order to avoid additional assumptions that might cast doubts on the reliability of the estimation within the insurance industry,[36] we simply rely on the directly observable part of the

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[35] By market, we essentially mean a broad measure and proxy for the (real) economic activity such as a major stock index. Throughout the paper, we therefore interchangeably use the terms system and market as (almost) perfect substitutes.

[36] However, it is worth noting that Brownlees and Engle (2012) provide a series of robustness checks on the stability of the parametrization of the SRISK measure.

measure, i.e. the DMES, which is sufficient to provide information on the individual fragility of the individual institution with respect to market tail events, which in turn have potential systemic implications.[37]

In addition, for each systemic risk measure and for each group, we compute the average contribution of the individual institution towards the total system composed by the three groups.[38] We then calculate the average contribution of each industry by taking the median of the month (for the ΔCoVaR and the DMES, whereas the Granger causality test is calculated on a monthly basis) and the average through the institutions of the same industry.[39]

Finally, at each point in time, we rank the institutions systemic relevance with respect to the total system from the most to the least systemically relevant according to each measure. We then select the top ten institutions at each point in time and calculate the relative weight of each industry within the top ten over time, thereby creating three indexes. Finally, we group all three indexes and form the Industry Composition Index displaying in percentage the top ranked institutions by industry.

4. Data

The data set for the industry analysis consists of equity returns of 60 companies listed in Europe over a time window of 14 years, from January 1999 to December 2013, which is 17 years (i.e. from January 1996 to December 2013) for the Granger causality test due to the lag on the series.[40] For each control group, we select the top 20 institutions in terms of capitalization from STOXX® Euro 600 Banks, STOXX® Euro 600 Insurance and STOXX® Europe 600 for banks, insurers and non-financials respectively.[41]

Table 1, displayed in Annex A.3, reports the list of the selected institutions for each group.

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[37] Another major issue we face regarding the estimation of the SRISK is the frequency of the accounting data: since we focus on European insurers, we do not possess sufficiently long quarterly series of balance sheet data.

[38] An extensive mathematical explanation of how the three cases are calculated is provided in Appendix A.1

[39] A formal representation of the index's construction is provided in Appendix A.3

[40] Data was downloaded from Datastream®

[41] Within each control group, companies are ranked according to the yearly average market capitalization over the 14-year time frame. We selected those companies which were continuously listed over the period. The list of the companies included in each group is reported in Appendix A.3

Data were collected both at daily and monthly frequencies. To calculate the ΔCoVaR, we rely on a set of state variables as proposed in Adrian and Brunnermeier (2011), namely i) Market volatility (VIX for Europe), ii) Liquidity spread (3M Repo - 3M Bubill), iii)} change in the short-term interest rate (3M Bubill), iv) the slope of the yield curve (10Y Bund - 3M Bubill), v) credit spread (BAA 5-7Y Corporate (Bank of America) - EURO Sovereign 5-7Y (Barclays)), vi) market returns (STOXX EURO 600 All shares).

5. Empirical results

5.1. The Granger causality test (Billio et al., 2012)

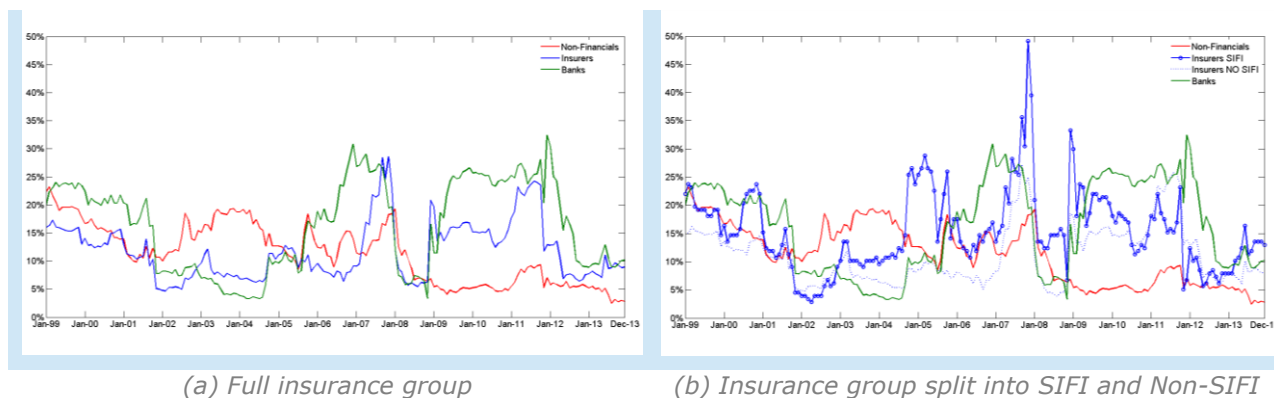| (a) Full insurance group | (b) Insurance group split into SIFI and Non-SIFI |

Figure 1: Total cause connections towards total system.
The figure displays for each group the number of significant cause and receives linear Granger causality connections over the total number of possible cause and receive connections. The statistical significance level is set at 5%. Results are calculated using Newey West standard errors.

Figure 5.1a above reports the evolution over time of the total number of causing (Granger-causal) significant connections over the total number of possible connections from each group towards the total system.

During the pre-crisis period the measure reports a generalized decrease in the connectivity level across the three groups: particularly in the period from 1999 to the end of 2004, the level of connectivity goes from roughly 20%-25% to 10%-15%. Starting form 2005 the graph shows a general increase of the significant connections that move to average values of 20%-25% with peaks of 35% in the beginning of 2007 and 2012. Looking at the single curves it is worth noting how during tranquil periods, namely in a low level relevant connection environment, the non-financial sector tends to play a more active role in comparison to the financial sector. The opposite occurs when the financial crises approach: financial companies almost doubled the number of relevant causing connection. As a matter of fact, starting from 2008 when Lehman Brothers filed for bankruptcy and American International Group (AIG) was bailed out, the index signals a small increase for non-financial and a jump in the connectivity

level for the financial service industry. This is evidence that these two events represent more of a shock to the financial industry than to the non-financial industry. Among the financial sector insurers display always a lower level of connectivity with respect to banks.

Figure 5.1b above reports the average results for those insurers labelled as SIFIs: this distinction is particularly relevant since regulators indicated some common characteristics among these institutions which should make them more systemically relevant compared to the median insurer. Results show a higher average degree of causality compared to the non-SIFI group with observable significant peaks during the Lehman Brothers bankruptcy and AIG bailout. In general, we can see that despite a higher causality compared to non-SIFIs, this sub-group of institutions still tends to play a minor role compared to banks in the aftermath of the Lehman crisis.

In summary, the outcome provided by the Granger causality test gives a fairly clear picture over time of who causes systemic risk: non-financials behave as a source of systemic risk during tranquil periods, whereas banks appear to be the most prominent cause in the aftermath of the crises. In particular, among financial institutions, insurers display an ambiguous behaviour and on average play a subordinated role compared to banks, especially during the 2007-2009 financial crisis and its aftermath. This is in line with existing findings for American insurance companies.[42] Findings apply both to non-SIFI and SIFI insurers, with the SIFI insurers reporting higher degree of causality than non-SIFI insurers, but on average lower than banks.
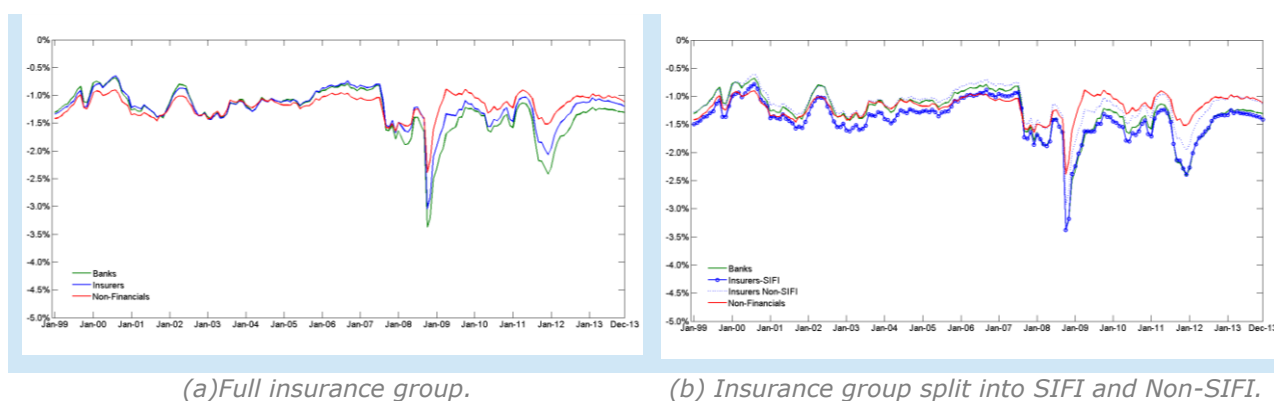
5.2. ΔCoVaR (Adrian and Brunnermeier, 2011)

(a)Full insurance group. *(b) Insurance group split into SIFI and Non-SIFI.*

Figure 2: Average institutions' ΔCoVaR towards total system.

The figures display the industry monthly average calculated on single institution's median value.

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[42] See, among others, Chen et al. (2013).

Figure 5.2a reports the results of the average individual institutions' ΔCoVaR towards the total system. The figure displays slight differentiation between financial and non-financial institutions with the curves almost perfectly co-moving up to mid-2007. From 2007 onwards the curves start to diverge: after the crises, the contribution to systemic risk of financial institutions increases dramatically, with banks once again dominating insurers in terms of marginal contribution. Even though the differences appear modest, we should stress the fact that the measure is estimated on daily returns and averaged through many institutions. Therefore the average marginal contribution of banks after 2008 can be estimated as being roughly 20% higher compared to insurers, which leaves it significantly higher.

Figure 5.2b reports a widespread increase of systemic contribution of SIFI insurers measured by CoVaR in comparison to the non-SIFI sample and even compared to banks. As a matter of fact, before the crisis SIFIs could be identified as the most systemically relevant institutions, whereas in the aftermath of the 2007 crisis their level of systemic relevance substantially matches the level displayed for banks.

In summary, ΔCoVaR provides a fairly clear indication of the behaviour of financial and non-financial institutions, which is in line with the Granger causality test. Besides, once more, insurers tend to play a subordinated role compared to banks, with the exception of a SIFIs' subsample that reports a high degree of systemic relevance, i.e. being highest in tranquil periods and providing almost the same contribution as banks during crises.

5.3. DMES (Brownlees and Engle, 2012

(a)Full insurance group.   (b) Insurance group split into SIFI and Non-SIFI.
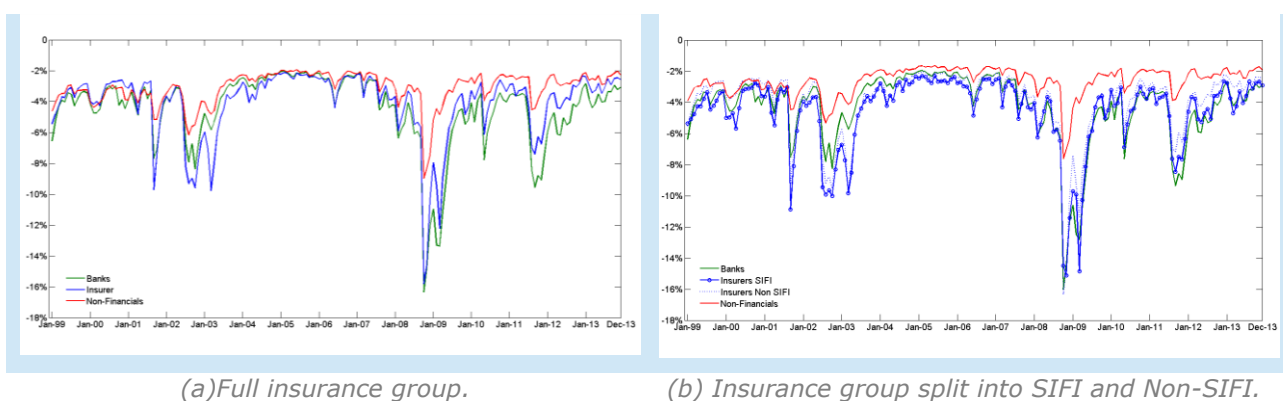
Figure 3: Average institutions' DMES towards total system.
The figures display the industry monthly average calculated on single institution's median value.

Figure 5.3a reports the results for the average marginal contribution of the individual institution towards the whole system. The pattern of each group is comparable with

the one obtained with the other two measures, in particular with the ΔCoVaR. The two measures present the same peaks during the financial crises and report a higher level of systemic riskiness after the crises compared to the pre-crises period. Differences from the previous measures can be found in the spikes at the end of 2001 and 2003 reported by DMES: these spikes are mainly driven by the insurance industry and can be traced back to industry-specific events such as 9/11 and severe natural catastrophes occurring in Europe in 2003. Consistent with the design of the measure, these peaks are well captured by DMES due to its focus on the tail of the distribution, i.e. severe events. In general, financial institutions report lower average DMES values than non-financial institutions, with some differences between banks and insurers depending on the period: in the aftermath of the crises, banks pose more risk than insurers.

Figure 5.3b reports the result for the DMES highlighting the behaviour of SIFIs: among the three measures, the DMES displays the smallest differences between SIFI and non-SIFI insurers. Moreover, in the period following the Lehman Brothers bankruptcy the systemic contribution of SIFI insurers remain inferior to the contribution of banks. Such an outcome stems from the high weight attributed by the measure to extreme events that affect the whole insurance industry's companies independently by being or not SIFIs. In summary, the DMES confirms the results obtained from the other two measures, attributing a higher systemic relevance to financial institutions, among which insurers prevail before Lehman Brothers and banks in its aftermath. Insurers display a higher systemic relevance than banks only for specific severe events properly captured by the measure. The measure, due to its construction, does not distinguish between SIFI and non-SIFI insurers over the observed time frame.
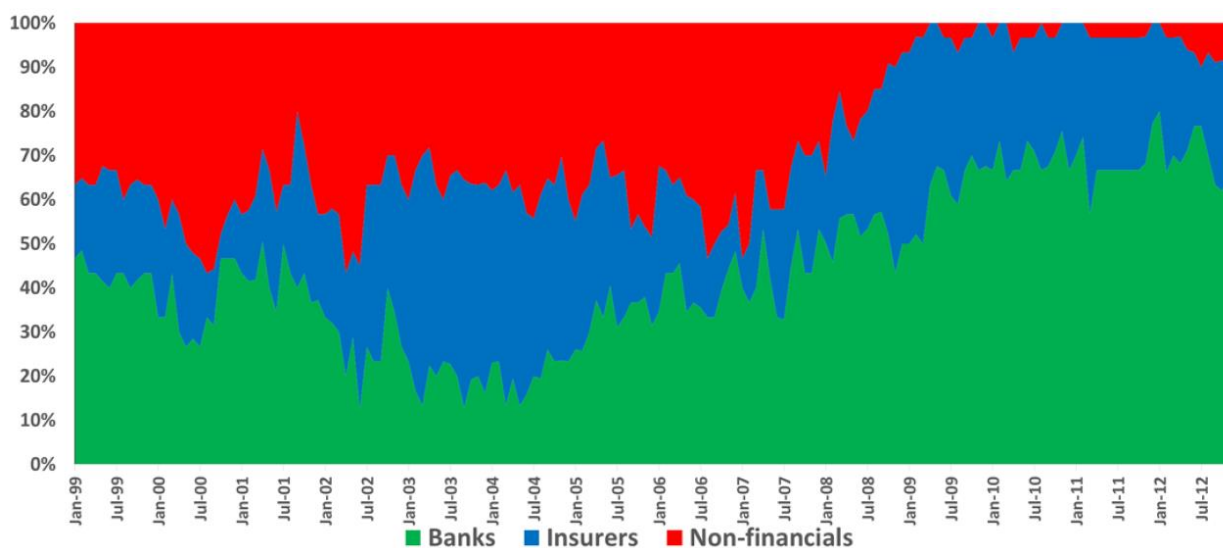
5.4. Industry Composition Index

Figure 4: Cumulative index.

The graph reports the average industry composition of the 3 indices at each point in time.

In order to provide a straightforward representation of the systemic relevance of the three groups according to the three measures, we display in Figure 5.4 the ten most systemically relevant institutions grouped by industry at each point in time. The systemic relevance of the three groups is summarized into a synthetic indicator that displays at each point in time the industry composition of the top ten most systemic institutions.[43]

The index clearly shows the alternative role of banks and non-financial companies over the observed period with non-financials dominating the index before Lehman, whereas banks dominate it thereafter. Insurers always tend to play a subordinated role both before and after the Lehman bankruptcy with respect to non-financial and to banks. However, it is worth noting that insurers are persistently present among the top ten systemic relevant institutions all over the observed period: if banks tend to replace non-financial institutions in the aftermath of the crises the number of insurance companies remains almost constant. Moreover, the progressive disappearing of non-financial companies from the top ten in the aftermath of the crisis and the European sovereign debt crisis that followed, allows appreciating the financial nature of these crises.

Concluding, we can summarize our findings: i) the three measures make a clear distinction between financial and non-financial institutions; ii) among financial institutions, banks dominate insurers in terms of contribution to systemic risk in the

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[43] See equation 24 in Appendix A2

aftermath of the crises, with insurers still displaying a persistent contribution to systemic risk over time; iii) there is no clear-cut evidence on higher systemic relevance of SIFI insurers; iv) trends in systemic risk contributions are time-dependent and tend to change rapidly, making the choice of the time span of analysis a crucial variable. Moreover, it is worth mentioning that the three measures were developed to capture different features of the systemic risk contribution of institutions, therefore inconsistencies over time should not be seen as lack of accuracy, but rather as emphasis on different factors that contribute to systemic risk.

6. Conclusion

In the present work, we propose an analysis of the role of the insurance industry in posing systemic risk. We conduct an aggregated industry analysis based on three measures of systemic risk on three different groups, Banks, non-financials and insurers operating in the European market. By doing so, we aim to test the relative systemic risk contribution of the insurance industry vis-á-vis other industries.

Our evidence suggests that financial institutions tend to cause more systemic risk than non-financial institutions and among financial institutions, banks pose more systemic risk than insurers, especially in the aftermath of crises.

Results are then summarized in the index reporting the top ten institutions by systemic relevance over time. The graphs show how the role of financial institution became preponderant after the crises and that despite the subordinate role of the insurers to banks, insurers are the most persistent companies over the observed period.

In addition we computed the contribution to systemic for the sub-sample of SIFI insurers. The Granger based measure and CoVaR distinguish between SIFIs and non-SIFIs, whereas DMES does not. Therefore our results do not allow inferring clear-cut evidence on the higher contribution to systemic risk posed by SIFI compared to non-SIFI insurers.

Our results provide a contribution to the debate on the systemic relevance of the insurance industry: this is particularly relevant in the light of the ongoing discussion on the role of SIFIs and on the specific regulations they might be subjected in the future.

Appendix

A.1 Systemic Risk Measures

The Granger causality test (Billio et al., 2012)

We measure the systemic importance of an institution in terms of the total number of statistically significant pairwise connections based on linear Granger causality tests. This approach allows us to infer when equity price movements of an institution influence price movements of another institution over a given period of time.

The Granger causality test measures the ability of two time series to forecast each other. We can write the system of equations as follows

$$y_{t+1}^i = \alpha^i y_t^i + \beta^{ij} y_t^j + \varepsilon_{t+1}^i \tag{1}$$

$$y_{t+1}^j = \alpha^j y_t^j + \beta^{ji} y_t^i + \varepsilon_{t+1}^j \tag{2}$$

in which coefficients α^i, β^{ij}, α^j, β^{ji} are estimated via linear regression and in which time series j is said to "Granger-cause" times series i if lagged values of j contain statistically significant information that helps in predicting i.

The causality indicator is defined as follow:

$$i \rightarrow j = \begin{cases} 1, & if\ j\ Granger\ cause\ i \\ 0, & otherwise \\ 0, & for\ j \rightarrow j \end{cases} \tag{3}$$

Equation three allows us to calculate a series of indexes based on the total number of significant relations among institutions at a specific point in time.[44] The Degree of Granger Causality thus represents the fraction of statistically significant relationships over the total number of possible connections among the full sample,

$$DGC = \frac{1}{N(N-1)} \sum_{i=1}^n \sum_{j \neq n} (j \rightarrow i) \tag{4}$$

Moreover, we can differentiate between causing and receiving connections which are defined as follows:

$$Out: (j \rightarrow S)|_{DGC \geq K} \ \frac{1}{N-1} \sum_{i \neq j} (j \rightarrow i)|_{DGC \geq K} \tag{5}$$

$$In: (S \rightarrow j)|_{DGC \geq K} \ \frac{1}{N-1} \sum_{i \neq j} (i \rightarrow j)|_{DGC \geq K} \tag{6}$$

We then compute the number of statistically significant in and out connections of one institution with respect to the total system:

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[44] The level of significance k is set at 0.05.

$$(j \rightarrow S^{-j})|_{DGC \geq K} \quad \frac{1}{3N-1} \sum_{i \neq j} (j \rightarrow S^{-j})|_{DGC \geq K} \tag{7}$$

$$(S^{-j} \rightarrow j)|_{DGC \geq K} \quad \frac{1}{3N-1} \sum_{i \neq j} (S^{-j} \rightarrow j)|_{DGC \geq K} \tag{8}$$

The two indexes represent the contribution of each individual institution. We then calculate industry averages by summing the total number of institutions' connections across each group.

<u>ΔCoVaR (Adrian and Brunnermeier, 2011)</u>

The measure extends the concept of Value at Risk (VaR) designed for individual institutions to the system as a whole. The CoVaR represents the VaR of a system conditional on institutions being in distress. The systemic contribution of an individual institution to the system is computed as the difference between the CoVaR of the institution in distress and the CoVaR in the median state, hence ΔCoVaR.

Following Adrian and Brunnermeier (2011), we calculate the ΔCoVaR using quantile regressions by setting the median state at the 50 percentile and the distress situation at the 95 percentile. We also include in the regressions a set of 6 state variables M_{t-1}, namely market volatility, liquidity spread, changes in the short-term interest rates, the slope of the yield curve, credit spreads and total equity returns, using one week lag.

Estimations are based on the following equations

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \tag{9}$$

$$X_t^S = \alpha^{S|i} y_t^j + \beta^{S|i} X_t^i + \gamma^{S|i} M_{t-1} + \varepsilon_t^{S|i} \tag{10}$$

where i represents the individual institution and S is the index representing the set of institutions under consideration. The predicted values from the regressions are then plugged into the following equation to obtain both the VaR of the individual institution and consequently the CoVaR:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{11}$$

$$CoVaR_t^i(q) = \hat{\alpha}^{S|i} y_t^j + \hat{\beta}^{S|i} VaR_t^i(q) + \hat{\gamma}^{S|i} M_{t-1} \tag{12}$$

Finally, the contribution of each institution to the system is calculated as follows:

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(5\%) - CoVaR_t^i(50\%) = \hat{\beta}^{S|i}(VaR_t^i(5\%) - VaR_t^i(50\%)) \tag{13}$$

The total system is defined as follow:

$$X_t^S = \frac{\sum_{j \neq i} \omega_{t-1}^j r_t^j}{\sum_{j \neq i} \omega_{t-1}^j} \tag{14}$$

with ω =market capitalization, r= return, j= total system,

$$\overline{\Delta CoVaR}_t^{total\ system|i} = \frac{1}{N}\sum_i^N \Phi^{-1}(0.5)\Delta CoVaR_{t\rightarrow t+h}^{total\ system|i} \tag{15}$$

where $t \rightarrow t+h$ indicates 1 calendar month of daily ΔCoVaR and N represents the number of institutions for each of the 3 groups. In order to avoid correlation biases we exclude institution i from the index representing the reference group.

DMES (Brownlees and Engle, 2012)

The measure is based on the expected loss conditional to a distressed situation (e.g. returns being less than a certain quantile): Brownlees and Engle (2012) extend the measure proposed by Acharya et al. (2010) by introducing a dynamic model characterized by time varying volatility and correlation as well as nonlinear tail dependence. The market model is defined as follows

$$r_{mt} = \sigma_{mt}\epsilon_{mt} \qquad .$$

$$r_{it} = \sigma_{it}\rho_{it}\epsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it} \tag{16}$$

$$(\epsilon_{mt},\xi_{mt})\sim F \qquad .$$

where r_i is the market return of the ith institution and σ_{it} is its conditional standard deviation, r_m is the market return of the system considered and σ_{mt} is its conditional standard deviation, ϵ and ξ are the shocks that drive the system and ρ_{it} is the conditional correlation between i and m.

The one period ahead DMES can be expressed as follows

$$DMES_{it-1}^1(C) = \sigma_{it}\rho_{it}E_{t-1}\left(\epsilon_{mt}\Big|\epsilon_{mt}<\frac{C}{\sigma_{mt}}\right) + \sigma_{it}\sqrt{1-\rho_{it}^2}E_{t-1}(\xi_{it}|\epsilon_{mt}<\frac{C}{\sigma_{mt}}) \tag{17}$$

where C is the conditioning systemic event which we assume to be equal to the 95th percentile of the total period market return, i.e. $C = \Phi^{-1}(0.95)r_m$.[45] The conditional standard deviations and the conditional correlation are estimated by means of a TARCH and a DCC model respectively.[46] The tail expectations $E_{t-1}\left(\epsilon_{mt}\Big|\epsilon_{mt}<\frac{C}{\sigma_{mt}}\right)$ and $E_{t-1}\left(\xi_{mt}\Big|\epsilon_{mt}<\frac{C}{\sigma_{mt}}\right)$ are calculated by means of a non-parametric kernel estimator and are given by the following equations:

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[45] The choice over the $VaR_{0.95}$ of the market allows for a more direct comparison with the estimations of the ΔCoVa For further mathematical details, see Brownlees and Engle, 2012.R.

[46] For further mathematical details, see Brownlees and Engle, 2012.

$$\hat{E}_h(\epsilon_{mt}|\epsilon_{mt} < k) = \frac{\sum_{i=1}^{n} \epsilon_{mt} K_h(\epsilon_{mt} - k)}{(n\hat{p}_h)} \tag{18}$$

$$\hat{E}_h(\xi_{mt}|\epsilon_{mt} < k) = \frac{\sum_{i=1}^{n} \xi_{mt} K_h(\epsilon_{mt} - k)}{(n\hat{p}_h)} \tag{19}$$

$$\hat{p}_h = \frac{\sum_{i=1}^{n} K_h(\epsilon_{mt} - k)}{n} \qquad \qquad .$$

The total system is defined as follow:

$$r_{mt} = \frac{\sum_{j \neq i} \omega_{t-1}^{j} r_{t}^{j}}{\sum_{j \neq i} \omega_{t-1}^{j}} \tag{20}$$

with ω=market capitalization, r= return, j= total system,

$$\overline{DMES}_{t}^{total\ system|i} = \frac{1}{N} \sum_{i}^{N} \Phi^{-1}(0.5) DMES_{t \to t+h}^{total\ system|i} \tag{21}$$

where $t \to t + h$ indicates 1 calendar month of daily DMES and N represents the number of institutions for each of the 3 groups. In order to avoid correlation biases we exclude institution i from the index representing the reference group.

A.2 Industry Composition Index

The group of selected institutions at each point in time is defined as

$$S_t^k = \left\{ i_{1,t} > \cdots > i_{n,t} > \cdots > i_{10,t} \right\} \tag{22}$$

in which i_n represents an institution ranked from the most to the least systemic (with $n = 1 \to most\ systemic$) according to the k measure, with k = Granger, ΔCoVaR, DMES. Then, the index for each systemic risk measure k is obtained as follows

$$I_t^k = \begin{cases} \frac{\sum_{n=1}^{10} \mathbb{I}_{i_{n,t}=Bank}}{10} \\ \frac{\sum_{n=1}^{10} \mathbb{I}_{i_{n,t}=Insurer}}{10} \\ \frac{\sum_{n=1}^{10} \mathbb{I}_{i_{n,t}=Non-Financial}}{10} \end{cases} \tag{23}$$

in which $\mathbb{I}$ is an indicator function that takes value 1 if the condition (e.g. if $i_n = Bank$) is met and 0 otherwise. Sums are then scaled between 0 and 1.

Finally, we group all three indexes and form the total index, which is given by

$$I_t^k = \begin{cases} \frac{\sum_k \sum_{n=1}^{10} \mathbb{I}_{i_{n,k,t}=Bank}}{10} \\ \frac{\sum_k \sum_{n=1}^{10} \mathbb{I}_{i_{n,k,t}=Insurer}}{10} \\ \frac{\sum_k \sum_{n=1}^{10} \mathbb{I}_{i_{n,k,t}=Non-Financial}}{10} \end{cases} \tag{24}$$

A.3 Tables

Table 1: List of the institutions included in the three control groups.

Banks		Insurers		Non-Financials	
name	*country*	*name*	*country*	*name*	*country*
HSBC HDG.	UK	ALLIANZ	DE	BP	UK
BANCO SANTANDER	ES	PRUDENTIAL	UK	VODAFONE GROUP	UK
UBS 'R'	CH	AXA	FR	NOVARTIS 'R'	CH
BNP PARIBAS	FR	ZURICH INSURANCE GROUP	CH	NESTLE 'R'	CH
LLOYDS BANKING GROUP	UK	MUENCHENER RUCK.	DE	GLAXOSMITHKLINE	UK
ROYAL BANK OF SCTL.GP.	UK	SWISS RE	CH	ROYAL DUTCH SHELL A	UK
BARCLAYS	UK	ING GROEP	NL	TOTAL	FR
CREDIT SUISSE GROUP N	CH	ASSICURAZIONI GENERALI	IT	ROCHE HOLDING	CH
BBV.ARGENTARIA	ES	SAMPO 'A'	FI	ENI	IT
DEUTSCHE BANK (XET)	DE	LEGAL & GENERAL	UK	TELEFONICA	ES
UNICREDIT	IT	AVIVA	UK	SANOFI	FR
SOCIETE GENERALE	FR	AEGON	NL	NOKIA	FI
STANDARD CHARTERED	UK	MAPFRE	ES	SIEMENS (XET)	DE
INTESA SANPAOLO	IT	HANNOVER RUCK.	DE	ASTRAZENECA	UK
NORDEA BANK	SE	AGEAS (EX-FORTIS)	BE	L'OREAL	FR
KBC GROUP	BE	RSA INSURANCE GROUP	UK	E ON (XET)	DE
DANSKE BANK	DK	VIENNA INSURANCE GROUP A	AT	BRITISH AMERICAN TOBACCO	UK
COMMERZBANK (XET)	DE	SCOR SE	FR	RIO TINTO	UK
SVENSKA HANDBKN.'A'	SE	SWISS LIFE HOLDING	CH	LVMH	FR
SEB 'A'	SE	BALOISE-HOLDING AG	CH	DIAGEO	UK

▭ : Systemically important insurance company

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