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Size is everything: Explaining SIFI designations

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ABSTRACT

In this paper, we study the determinants of the systemic importance of banks and insurers during the financial crisis. We investigate the methodology of regulators to identify global systemically important financial institutions and find that firm size is the only significant predictor of the decision of regulators to designate a financial institution as systemically important. Further, using a cross-sectional quantile regression approach, we find that Marginal Expected Shortfall and ΔCoVaR as two common measures of systemic risk produce inconclusive results concerning the systemic relevance of banks and insurers during the crisis.

Keywords: Systemic risk, interconnectedness, systemic relevance, financial stability.
JEL Classification: G01, G20, G28.

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1 Introduction

At the climax of the financial crisis of 2007-2009, American International Group (AIG) became the first international insurer that required (and ultimately received) a bailout as regulators considered AIG to be too systemically important to default. At the time, AIG's near-collapse came to the surprise of most analysts and financial economists as systemic risk was considered to be a problem confined to banking, but not insurance. As a response to this wakeup-call, regulators have recently started to realign the regulation of international insurance companies towards a macroprudential supervision. Most prominently, on July 18, 2013, the Financial Stability Board (FSB) in collaboration with the International Association of Insurance Supervisors (IAIS) published a list of nine Global Systemically Important Insurers (G-SIIs) which will ultimately face higher capital and loss absorbency requirements. In essence, regulators deem insurers to be globally systemically important in the views of regulators if they are of such size and global interconnectedness that their default would trigger severe adverse effects on the financial sector. Previously, in November 2011, the FSB had similarly identified a set of 29 banks as Global Systemically Important Financial Institutions (G-SIFIs). However, the validity of these classifications and the actual determinants of the decision of regulators to designate a financial institution as global systemically important remain relatively unknown.

Until the financial crisis, economists had never expected systemic risks to arise from the insurance sector. In contrast to banking, insurance companies are not vulnerable to runs by customers and thus are not subject to sudden shortages in liquidity. Although theoretically, one could think of runs on life insurance policies, there has not been a single example in history for such a run to take place and cause systemwide defaults of insurers (see, e.g., Eling and Pankoke, 2014).[1] Furthermore, even the largest international insurers are significantly smaller in size, less interconnected, and hold more capital (see Harrington, 2009) than the largest global banks. In light of this, the case of AIG seems to have been a major exception to the rule that insurers do not cause systemic risks.

[1] An "insurer run" is regarded as unlikely by most economists as customers are often protected by guarantees that are similar to explicit deposit insurance schemes in banking.

As insurers do not accept customer deposits, they do not face the risk of a sudden shortage in liquidity due to a bank run. In addition, insurers in contrast to banks often rely more strongly on long-term liabilities thus further decreasing their exposure to liquidity risk. Furthermore, insurers are said to be less interconnected than banks resulting in a lower probability of contagion among insurers (see Bell and Keller, 2009). Based on the experiences from the financial crisis, the IAIS (2013) published a methodology for assessing the systemic risk of international insurers. In this methodology, the key determinants of systemic risk in insurance are non-core and non-insurance activities, insurer size and interconnectedness.[2]

However, the empirical evidence on the questions whether insurers can become systemically relevant and whether these factors drive systemic risk is limited. Shortly after the financial crisis, Acharya et al. (2009), Harrington (2009), and Cummins and Weiss (2014) discussed the role of insurers during the financial crisis.[3] More recently, due to the increased attention regulators are giving this topic, several studies have analyzed different aspects of systemic risk in insurance. For example, Cummins and Weiss (2014) and Weiß and Mühlnickel (2014) study the effect of different factors from the IAIS methodology on the systemic risk of U.S. insurers. In addition, Mühlnickel and Weiß (2015) support the too-big-to-fail conjecture for insurers by showing that insurer mergers tend to increase the systemic risk of the acquiring insurers.

In this paper, we analyze the question whether common measures of systemic risk are significantly driven by the size, the interconnectedness, and the leverage of global banks and insurers. As systemic risk measures, we employ the institutions' Marginal Expected Shortfall (MES) (see Acharya et al., 2010) and their ΔCoVaR (see Adrian and Brunnermeier, 2014). We then perform separate quantile regressions for both a sample of the world's largest banks and insurers of these two measures of systemic risk on size, interconnectedness, leverage, and a set of control variables.

[2] The non-core activities listed by the IAIS include credit default swaps (CDS) transactions for non-hedging purposes, leveraging assets to enhance investment returns, as well as products and activities that concern bank-type (or investment bank-type) activities. Furthermore, the IAIS argues that insurance companies which engage in non-traditional insurance activities are more affected to financial market developments and contribute more to systemic risk of the insurance sector.

[3] Additional analyses of systemic risk in insurance are due to Eling and Schmeiser (2010); Lehmann and Hofmann (2010), and van Lelyveld et al. (2011).

For both banks and insurers, the results of these quantile regressions are counterintuitive to the current standpoint of regulators. The extreme quantiles of both MES and ΔCoVaR (i.e., institutions that are most exposed and contribute the most to systemic risk) are not significantly affected by size. Higher leverage and interconnectedness are only weakly significantly related to systemic risk and seem to decrease the systemic relevance of financial institutions. We then turn to probit regressions of the probability of membership in the groups of G-SIFIs and G-SIIs. Our results are extremely revealing: the decision of regulators to declare a financial institution (bank or insurer) as systemically relevant is only driven by the institution's size.

The rest of this paper is structured as follows. Related literature is presented in Section 2. The data and variables used in our empirical study are discussed in Section 3. The outline and the results of our analysis are given in Section 4. Section 5 concludes.

2 Related literature

The case of systemic risk in the banking sector has been discussed extensively in the recent literature. However, the question whether insurers can actually become systemically relevant for the financial system and the question whether the IAIS's proposed methodology is suitable for identifying G-SIIs remain relatively unanswered in the literature so far. Only few studies focus on the exposure and contribution of insurers to systemic risk and the key determinants that could cause severe consequences for insurers. Reviewing the academic literature, Trichet (2005) argued that the traditional insurance business is not vulnerable to "insurance runs" and that interconnectedness in the insurance sector is weak in contrast to the banking sector. After the financial crisis this view changed significantly. For example, Baluch et al. (2011) conclude that systemic risks exist in the insurance sector even though they are smaller than in banking. More importantly, systemic risk in insurance appears to have grown partially as a consequence of the increasing interconnectedness of insurers to other financial institutions and their activities outside of the traditional insurance business. Further, Trichet (2005) argues that new non-traditional insurance activities, for example, writing credit derivatives, can cause contagion in the financial sector. A warning that came almost three years before the near-collapse of AIG.

In the empirical literature, several studies have focused on the the interconnectedness of insurers as a primary driver of systemc risk. Billio et al. (2012) analyze the interconnectedness of global financial institutions based on their stock prices. They argue that illiquid assets of insurers could create systemic risks in times of financial crisis. In a related study, Chen et al. (2014) analyze the interconnectedness of banks and insurers but find in their analysis of credit default swap and intraday stock price data that the insurance sector is exposed to but does not contribute to systemic risks in the banking sector.

While the former two studies only address the interconnectedness of banks and insurers, the effect of additional factor like size, leverage, and profitability on systemic risk in the insurance sector is studied by Weiß and Mühlnickel (2014).[4] Most importantly, they find that insurer size has been a major driver of the systemic risk exposure and contribution of U.S. insurers. Several of the IAIS indicators (e.g., geographical diversification), however, do not appear to be significantly related to the systemic risk of insurers. The hypotheses behind these suspected causal relations are similar to arguments brought forward in banking. Insurer size, for example, could have an increasing effect on systemic risk in the insurance sector, because larger insurance companies have a wider range of different risks covered and thus are less prone to suffer from cumulative losses (see Hagendorff et al., 2014). Yet, larger insurance companies could become too-interconnected-to-fail and thus systemically relevant (see Acharya et al., 2009).

Additionally, the IAIS has also argued that high leverage could increase the systemic importance of individual insurers (especially in combination with size and interconnectedness). High leverage incentivizes managers into excessive risk-taking to increase a firm's profitability (see, e.g., Acharya et al., 2010; Fahlenbrach et al., 2012). However, leverage is obviously not bad per se. For example Vallascas and Hagendorff (2011) stress the disciplining function of leverage as it pressures managers into securing the payments of interest to investors and to secure a firm's

[4] In a related study, Cummins and Weiss (2014) also analyze the characteristics of U.S. insurers that are systemically important.

liquidity. In addition, insurers that engage too heavily in non-core activities such as derivatives trading could also single-handedly destabilize the financial sector. For example, one of these non-traditional activities identified by the IAIS is the use of catastrophe bonds to hedge against severe losses induced by natural catastrophes. The assumption that these hedging vehicle could make insurers more interconnected with financial markets and thus more systemically relevant is confuted in Weiß et al. (2013). Concerning derivatives trading, Cummins and Weiss (2014) note that excessive derivatives trading by insurers was a major source of systemic risk in insurance during the financial crisis.

Probably the most fundamental question, however, remains whether systemic risk in insurance companies (if it even exists) is large enough to destabilize the whole financial sector. In this respect, Bierth et al. (2015) find systemic risk in the international insurance sector to be small in comparison to previous findings in the literature for banks. However, confirming the results of Baluch et al. (2011), they find a strong upward trend in both the exposure and contribution of insurers to the fragility of the global financial sector during the financial crisis. In further panel regressions, they find the interconnectedness of large insurers with the financial sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be primarily driven by the insurers' size and leverage.

3 Data

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

3.1 Sample construction

Balance sheet and income statement data are retrieved from the *Thomson Worldscope* database and all stock market and accounting data are collected in U.S. dollars to minimize a possible bias as a result from currency risk. To construct our sample, we select all publicly listed international insurers from the dead and active firm list in *Thomson Reuters Financial Datastream* and omit all firms for which stock price data are unavailable in *Datastream*. We exclude Berkshire Hathaway due to its unusual high stock price, although it is listed as an insurer in *Datastream*. For our analysis we restrict our dataset to the one hundred largest insurance companies, measured by their total assets at the end of the fiscal year 2006. A similar procedure is used for the construction of our international sample of banks. Initially, we start with a sample of all firms in the active and dead-firm "banks" and "financial services" lists in *Thomson Reuters Financial Datastream*. [5] As in Fahlenbrach and Stulz (2011), we then select all companies with SIC codes between 6000 and 6300 (i.e., we eliminate insurers, real estate operators, holding and investment offices as well as other non-bank companies in the financial service industry from our sample of banks). It is crucial for our analysis that we have accounting price and stock price data available in *Thomson Worldscope* and *Datastream*. Therefore, we therefore exclude firms for which these data are not available. We exclude a stock from our sample if it is identified in *Datastream* as a non-primary quote or if it is an American Depositary Receipt (ADR). All OTC traded stocks and preference shares are also removed. Similar to the insurer sample, we restrict our data set to the 150 largest banks, measured by their total assets at the end of the fiscal year 2006. Due to secondary listings, we have to remove another two banks and two insurers from the samples. The geographical distribution of our sample banks and insurers covers 36 countries with most banks (25 out of 148) and insurers (27 out of 98) being from the United States. Following the U.S., the four most prominent countries in our samples are China (10 banks/2 insurers), Japan (16/6), the United Kingdom (11/8), and Germany (8/11). The geographical spread of our sample firms is shown in Table I. [6] For increased transparency, the names of the 98 insurers and 148 banks in our final sample can be found in Appendix A.1 and A.2.

[Insert Table I about here.]

[5] Since we cannot rule out that some banks are erroneously listed in the "financial services" instead of the "banks" category in *Datastream*, we use both lists to generate our final sample.

[6] The names of the 98 insurers and 148 banks in our final sample are available upon request.

Next, we define and discuss the main dependent and independent variables for our analysis in the subsequent sections. Appendix A.1 gives an overview of all variable definitions and data sources used in our empirical study. To minimize the possibly biasing effect of extreme outliers in our sample on our results, all data are winsorized at the 1% and 99% levels.

3.2 Systemic risk measures

This study employs two different measures of systemic risk that proxy for an institution's sensitivity or exposure and contribution to systemic risk in a larger financial system. Systemic risk is calculated for the crisis period which we define as the period between July 2007 and the end of december 2008 (see Fahlenbrach et al., 2012). Similar to the recent literature (see, e.g., Anginer and Demirgüç-Kunt, 2014; Anginer et al., 2014; Weiß and Mühlnickel, 2014), we use as our measures of systemic risk the unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2014) and the Marginal Expected Shortfall as defined by Acharya et al. (2010).

One of the more established measures of systemic risk that is also used by regulators is the unconditional ΔCoVaR measured as the difference of the Value-at-risk (VaR) of a financial sector index[7] conditional on the distress of a particular insurer and the VaR of the sector index conditional on the median state of the insurer. Therefore, ΔCoVaR can be interpreted as the actual contribution to systemic risk in the financial system by the respective observed company.

In contrast, the Marginal Expected Shortfall is defined as the negative average return on a firm's stock on the days an index (in our case the MSCI World index) experienced its 5% worst outcomes. [8] A positive MES thus indicates a positive exposure to systemic risk rather than a stabilizing effect.

7 In our main analysis, we employ the MSCI World Index. For further robustness checks, we also employ the the World DS Full Line Insurer Index, the MSCI World Banks Index, and the MSCI World Insurance index for the calculation of ΔCoVaR and Marginal Expected Shortfall.

8 Additionally, we employ the Dynamic Marginal Expected Shortfall calculated following the procedure laid out by Brownlees and Engle (2012) for robustness checks later on.

3.3 Explanatory variables

The focus of our analyses is to shed more light on the interplay of systemic risk and possible determining factors proposed by the Financial Stability Board and the IAIS (2013). Thus, we concentrate on size, leverage, and the interconnectedness of banks and insurers. We intend to show whether these factors can explain the decisions of regulators to propose global systemic relevance for some of the banks and insurers in the financial system. Furthermore, we compare the predictive power of these factors for explaining the cross-sectional variation in both the institutions' MES and ΔCoVaR.

As a standard proxy for size we employ the natural logarithm of an institution's total assets at the end of the fiscal year 2006. The effect of size on systemic risk could be ambiguous. On the one hand, if a bank or insurer is deemed "too-big-to-fail", and hence might receive subsidies from safety net policies in a situation of undercapitalization, this could incentivize managers to take more risks than socially optimal. Consequently, large banks or insurers are more likely to contribute significantly more to systemic risk than smaller institutions (see, e.g., O'Hara and Shaw, 1990; Acharya and Yorulmazer, 2008; Anginer et al., 2014). Additionally, Gandhi and Lustig (2015) find that, in contrast to non-financial firms, size is a priced factor in the cross-section of bank stock return. According to their study this is due to the pricing of implicit bailout guarantees by stock market investors. On the other hand, a larger firm generally has more opportunities to diversify and thus hedge against times of financial turmoil, which could decrease the firm's systemic risk.

As the next main variable of interest, we measure a firm's leverage as the book value of assets minus the book value of equity plus the market value of equity, divided by the market value of equity (see Acharya et al., 2010). High leverage is a factor that incentivizes managers into excessive risk-taking to increase a firm's profitability.[9] In contrast, managers could be disciplined by higher leverage since they could feel more pressured to provide enough liquid assets to cover interest pay-

[9] Support for this view is found by Acharya et al. (2010), Fahlenbrach et al. (2012) and Hovakimian et al. (2012) who empirically show that banks with low leverage during the crisis performed better and had less contribution to systemic risk than firms with high leverage ratios.

ments (see, e.g., Vallascas and Hagendorff, 2011). This could in turn decrease a bank's or insurer's total risk. We therefore include leverage as a main independent variable in our regressions with no prediction for the sign of the coefficient.

The third important factor entering our analyses is the interconnectedness of banks and insurers within the financial system. Since we do not have information on, e.g., interbank lending markets, we make use of the measure of interconnectedness of a financial institution proposed by Billio et al. (2012) based on standardized stock returns of individual banks and insurers.

Billio et al. (2012) propose an univariate measure *PCAS* of an institution's interconnectedness with the system (using all types of financial institutions) which is based on a principal component analysis of the correlations between all institutions' stocks. The measure then computes the contribution of an individual institution to the overall risk of the financial system. The more interconnected an insurer or bank is with the rest of the financial sector, the higher its systemic relevance will be. We therefore suspect PCAS to enter our regressions with a significant increasing effect on systemic risk (see Arnold et al., 2012; Black et al., 2013; IAIS, 2013). An interconnected financial institution will be more exposed to shocks within the system. However, being more intertwined with the system does not automatically translate into a higher contribution to the systemic risk itself. Furthermore, similar to the too-big-to-fail argument, the too-interconnected-to-fail hypothesis (see Arnold et al., 2012; Black et al., 2013; IAIS, 2013) states that institutions that are too-interconnected-to-fail are guaranteed a safety net by governments to fall back on. Consequently, our expectations for the impact of the interconnectedness variable are unrestricted.

In addition to our three main independent variables that cover the most important (presumed) driving factors of systemic relevance, we include in our regressions several firm-specific characteristics that have shown to be significant drivers of performance and systemic risk of banks and insurers in the recent literature. An overview of all the variable definitions, data sources and our hypotheses regarding the analyses is given in Appendix A.1.

We include a firm's annual buy-and-hold stock returns in 2006, since institutions that took on too many risks in the past could also stick to their culture of risk-taking (see Fahlenbrach et al.,

2012) and increase their exposure and contribution to systemic risk. Next, we include standard proxys for a firm's valuation (market-to-book ratio) and its profitability (return on assets) and expect them to decrease a bank's and insurer's systemic risk. The literature suggests that banks and insurers that relied heavily on short-term funding were exposed to liquidity risks during the recent financial crisis and increased their overall systemic risk (see Brunnermeier and Pedersen, 2009; Cummins and Weiss, 2014; Fahlenbrach et al., 2012). Consequently, we control for the degree to which an insurer or bank relied on long-term debt before the crisis (debt maturity).

Turning to the variables specifically related to the insurance business, we control for the success of an insurer's asset management (investment success) and whether the form of generated income (fixed income) influences systemic risk. If an insurance companies relies more on asset management rather than underwriting it could be more intertwined with the global financial markets and could thus contribute and be more exposed to global systemic risk. To check for other possible non-core activities we also include the variables non-policyholder liabilities and other income. Additional risk could arise in the form of poor management of the company which could also manifest itself in the quality of the insurance portfolio. We therefore include the variables loss ratio and operating expenses. Regarding our sample of banks, we use the composition of the bank's liabilities (deposits) to control whether banks with more deposit financing are in fact more stable. Next, we include the natural logarithm of expenses set aside as an allowance for uncollectable or troubled loans (loan loss provisions) to proxy for a bank's credit risk. A larger buffer against troubled loans should serve as a stabilizing factor for a bank's systemic risk. Also, we control for the loans-to-assets ratio (loans) of a bank, since it could indicate a business model that focuses on lending rather than more risky activities, which reduces systemic risk. With a similar reasoning, we include the ratio of non-interest income to total interest income (non-interest income) as a variable in our analysis. A bank relying more on non-deposit taking activities like, e.g., investment banking, could also be riskier than banks with a focus on traditional lending (see, e.g., Brunnermeier et al., 2012). Finally, we employ a bank's Tier-1-capital ratio (tier-1-capital) to check whether higher regulatory bank capital acts as a buffer against losses and stabilizes the individual bank within the financial sector.

3.4 Descriptive statistics

Table II shows summary statistics for our two dependent variables for the time period July 2007 to the end of 2008 (crisis period) and for our three main explanatory variables of interest: total assets, leverage, and interconnectedness in the year 2006.[10]

[Place Table II about here.]

The summary statistics for the banks in our sample are given in Panel A and for the insurers in Panel B of Table II. First, we notice that the means of the variables of the banking sector differ substantially from the insurance sector. The average MES is higher for insurers than for banks while the opposite is true for ΔCoVaR. One explanation for this finding could be the fact that both measures are purely based on stock market data. As insurers will most likely have a higher sensitivity of their asset side to downturns in equity markets, so will their own equity. Consequently, the higher estimates for MES of insurers could be indicative of a) a higher overall (average) systemic importance of insurers or b) a higher sensitivity of their equity to market crashes (which in part could also indicate a higher systemic risk). Conversely, the sheer size of the asset management activities of the larger insurance companies and crisis-related shifts in their asset portfolios could also explain the lower average ΔCoVaR in our sample.

Insurers have a mean of total assets of \$ 158 billion while banks are significantly larger with a mean of total assets of \$ 350 billion. Furthermore, the leverage of banks is on average 13.430 whereas the insurers have a mean leverage of 9.285, which underlines the increased leverage in banking compared to other industries. As expected, on average, banks had significantly higher total assets, leverage and were more interconnected than insurers. Additionally, we find only little evidence of strong interconnectedness of the insurers in our sample compared to the bank sample. Based on the univariate analysis, we hypothesize that size and leverage are the driving systemic

[10] Note that the sample size is slightly reduced by the unavailability of some balance sheet items for smaller banks and insurers in *Worldscope*.

risk while interconnectedness does not play such an important role for explaining differences in MES and ΔCoVaR.

4 The determinants of systemic relevance

This section investigates which (possibly differential) factors determine the systemic relevance of banks and insurers. We first present the results of our cross-sectional OLS and quantile regressions of the institutions' MES and ΔCoVaR during the crisis. Afterwards, we report and comment on the results of our probit regressions for the determination of factors that influence systemic relevance as stated by regulators.

4.1 Cross-sectional regressions

Instead of only using the standard OLS approach for cross-sectional regressions, we perform the multivariate analysis of the determinants of extreme values of MES and ΔCoVaR in two ways. In particular, we employ cross-sectional quantile regressions with bootstrapped standard errors[11] and simple OLS regressions with robust standard errors of our systemic risk proxies during the crisis on our (lagged) main independent and the various control variables in 2006. The use of quantile regressions benefits us with reasonable benefits compared to OLS regressions. OLS models the relationship between the conditional mean of the dependent variable and the independent variables. We do not include all active Banks and insurance companies with available data in *Datastream* because the values of our systemic risk measures (or the dummy variables for our probit regressions) would be distorted by the inclusion of too many firms in a mechanical way. The quantile regression approach by Koenker and Basset (1978) circumvents the problems that arise in OLS due to heteroskedasticity in the data by estimating the change in a specified quantile of the dependent variable given the covariates produced by the independent variables. Quantile regression models the quantiles of the dependent variable's distribution and therefore does not suffer from the

[11] By using bootstrapped standard errors, we are able to partially obviate possible biases by the non-i.i.d. character of our data.

usual heteroskedasticity problem. For the MES, we analyze the 95%-percentile and for ΔCoVaR we analyze in the 5%-percentile, with both indicating extreme systemic risk. The results of our cross-sectional analysis for banks are shown in Table IV and III.

[Insert Tables III and IV about here.]

The first three regressions in all settings are concerned with the individual effects of our three main dependent variables: size, leverage, interconnectedness with the financial system, as well as systemic risk.

In the OLS regressions of banks we find no significant effect of the variables total assets and leverage on our systemic risk measures except for a strong significance at the 1% level of interconnectedness on ΔCoVaR. Surprisingly, the variable enters the quantile regression with a positive coefficient and thus increases the value of ΔCoVaR (i.e., decreases the systemic risk contribution of the bank). We interpret this result as an indication that the market-based measure of interconnectedness that we use may be an imperfect proxy for a bank's interconnectedness. For example, it could be that our proxy does not adequately capture the risk concentration in the banking sector caused by banks' purchasing and holding similar assets like, e.g., mortgage-backed securities. By adding our control variables, we only lose some of the significance of the coefficient of interconnectedness and find no statistically significant influence of any other variable on ΔCoVaR. Looking at the respective quantile regressions on the 5%-quantile of ΔCoVaR reveals that only bank size is a slightly statistically significant predictor of extreme contribution of banks to systemic risk. The variable enters the quantile regression with a positive sign of the coefficient at a 10% level, which indicates the counterintuitive impression that larger banks contribute less to systemic risk. Again, this result points at the possibility that both our proxies for size and interconnectedness do not fully capture the main drivers of a bank's systemic risk.

The OLS regressions of MES on our main variables of interest show that only the interconnectedness influenced the exposure of banks to external shocks during the crisis. The coefficient of interconnectedness enters both the OLS and the quantile regression with a negative sign that is significant at the 1% level in the regression of the conditional mean and at the 10% level for the regression of the 95%-quantile. Thus, we find the result that being more interconnected does not necessarily increase the exposure of banks to systemic risk. Interestingly, we note a slightly significant decreasing effect of the variable deposits on MES which leaves us with the interpretation that banks with higher deposit financing were more stable and less sensitive to external shocks during the financial crisis.

The regressions of banks' systemic risk on the indicators of systemic relevance reveal that only the interconnectedness of banks with the financial sector helps in explaining the magnitude of the contribution or exposure to systemic risk. In Tables V and VI, we show the results from the OLS and quantile regressions of ΔCoVaR and MES on the proposed factors of systemic relevance for insurers.

[Insert Tables V and VI about here.]

Table V shows that an insurer's size decreases ΔCoVaR (significant at the 10% level) and thus, indicates a higher contribution to systemic risk by larger insurers. This significance, however, vanishes when including other control variables and is also never significant when regressing the conditional quantile of systemic risk. A very similar pattern can be found in Table VI concerning insurer size, where total assets to increase the exposure to systemic risk. On the other hand, we find that a higher leverage induces a lower systemic risk contribution. For the interconnectedness variable, we find the same effects on systemic risk as in the models involving our sample of banks, although with statistically less significant results.

Turning to the quantile regressions for our insurer sample, we notice that interconnectedness exhibits a strong influence on systemic risk. Although the actual values of interconnectedness of insurers are much lower than those for the sample of banks, we notice that being interconnected with the financial system as an insurer has a much stronger impact on the systemic risk of the insurer than for banks. The coefficients in the quantile regressions are positive for ΔCoVaR and negative for MES which indicates a decrease in the contribution and the exposure to systemic risk. This holds true at the 1% level. Again, this counterintuitive result could be due to our proxies of systemic risk not being able to fully capture all facets of an institution's systemic relevance.

Alternatively, it could be that our market-based proxy of interconnectedness does not pick up all causes of interbank linkages (e.g., due to ubiquitously held risky securities). Additionally, we find that profitability and higher loss ratios also have a decreasing effect on the contribution to systemic risk. Throughout all of the regressions neither size nor leverage consistently enter the analysis with a significant coefficient. Consequently, a simple analysis of MES and ΔCoVaR could lead to the conclusion that both size and leverage are not significant drivers of systemic risk in banking and insurance.

As mentioned earlier, the set of explanatory variables that we use in our regressions is strongly motivated by arguments of regulators that size, leverage, and interconnectedness are the main drivers of systemic risk. The weak explanatory power of these variables, together with the fact that the variables often have a counterintuitive effect on systemic risk, are indicative of a possible omitted variable bias in both our analysis as well as in the logic of regulators. As seen during the financial crisis, a major driver of systemic risk in the financial sector was the common practice of institutions to invest in asset- and mortgage-backed securities that caused a dangerous concentration of risk despite these instruments' top ratings. However, our analysis suggests that these potential drivers of systemic risk are neither reflected in size nor our market-based proxy for an institution's interconnectedness.

4.2 Probit regressions

In this section, we explain the probability of being declared a global systemically important bank or insurer by regulators. Employing a probit regression model allows us to explain the probability that a bank or an insurer will be declared systemically relevant or not. To this end, we employ the same set of explanatory variables as before in our quantile regressions.

The results of the probit regressions for the 148 largest banks, measured by their total assets in 2006, are presented in Table VII.

[Place Table VII about here]

Table VII shows the results of several probit regressions on dummy variables that take on the value of one if a bank was declared global systemically important by the Financial Stability Board and zero otherwise.

Starting with probit regressions (1) to (3) of systemic relevance of banks, we can see that neither the banks' leverage nor their interconnectedness are significant indicators of an institution's systemic importance. This first finding is in striking contrast to the hypotheses formulated by the Financial Stability Board on the pivotal role of leverage and interconnectedness for a bank's systemic relevance. It is, however, in line with the notion that risk concentrations in financial institutions' assets as seen during the financial crisis rather than leverage or interconnectedness alone could be responsible for systemic crises. Interestingly, our results in regression (4) imply that the banks' Marginal Expected Shortfalls has a significant influence on the global importance of a bank as perceived by regulators (from model (5) we see that ΔCoVaR is not statistically significant). In model specifications (6) and (7), we include several control variables in our regressions but only find size to be a driving factor for systemic importance. More precisely, the MES of the banks which previously entered the regression with a significant positive coefficient now loses all its statistical significance. Consequently, we find strong evidence that the nomination as a G-SIFI is only driven by the institution's size. As such, regulators appear to have based their decision to declare an institution as systemically relevant solely on the notion of a bank being too-big-to-fail.

The probit regression results for the sample of insurers are shown in Table VIII.

[Place Table VIII about here]

Similar to the results for the banks, we can see from the probit regressions (1) to (5) that neither the insurers' leverage nor their interconnectedness are significant indicators of the nomination as a G-SII by the FSB and the IAIS. These findings are also in striking contrast to the hypotheses of the pivotal role of leverage and interconnectedness for an insurer's systemic importance. In regression (5) we find an insurer's ΔCoVaR to be a significant determinant of the probability to be included in the list of G-SIIs. However, this effect vanishes as soon as we add total assets and other controls to our regression model. Similar to the probit regressions for banks, we find in regression (6) that size is the only reliable predictor of systemic relevance according to regulators. This holds true even when we include various control variables.

In summary, the results of our probit regression analyses show that the inclusion of an institution in the list of G-SIFIs or G-SIIs is only a question of size. While MES and ΔCoVaR do appear to capture some of aspects of systemic risk, these measures cannot explain the methodology proposed by regulators. They determine the systemic importance of a financial institution (regardless whether it is a bank or insurer) only by the institutions' size.

4.3 Robustness checks

To underline the validity of our results, we perform additional robustness checks. First, our results could be biased by the manner in which we calculate the systemic risk measures ΔCoVaR and Marginal Expected Shortfall. Reestimating the measures using the MSCI World Banks Index and MSCI World Insurance Index does not significantly change our main results. For our cross-sectional analysis, we reestimate the OLS and quantile regression models with alternative definitions of our key variables leverage (ratio of total liabilities to total assets) and size (natural logarithm of net revenues). Except for the OLS regression for banks of MES on control variables, where we find a statistical significance of leverage at the 10% level, our main inferences are robust to these changes. Also, to control for an insurer's line of business, we include a dummy variable in our cross-sectional analyses that is one if the company is a life insurer (SIC code 6311), and zero otherwise. Including this variable neither changes our main inferences, nor do we find it to be significant in most of the regressions. However, in the regression of an insurer's ΔCoVaR on the control variables, we find a positive relation of the life insurer dummy and ΔCoVaR that is significant at the 10% level indicating that life insurers in our sample have a lower contribution to systemic risk than non-life insurers. Finally, we reestimate our probit regressions for banks and insurers using data from later years, i.e., 2009 and 2010 (if available) as it could be argued that regulators identified systemically relevant financial institutions based on post-crisis data rather than data from 2006. Our additional analyses, however, reveal no new information and also suggest that size was the most common factor when constructing the list of systemically relevant institutions.

5 Conclusion

In this paper, we study the determinants of the systemic importance of the world's largest banks and insurers during the financial crisis. Using a sample of the largest 148 banks and 98 insurers in the world, we analyze the cross-sectional variation in two popular measures of systemic risk of financial institutions during the crisis. In the second step of our analysis, we try to explain the decision of regulators to include certain banks and insurers in the lists of global systemically important financial institutions and global systemically important insurers.

Our results show that our quantile regressions of banks' and insurers' MES and ΔCoVaR as our systemic risk proxies mainly produce counterintuitive results. We find little to no evidence that higher leverage and interconnectedness increase the exposure or contribution of individual institutions to systemic risk. However, both measures are based purely on balance-sheet and stock market data and thus could be missing other drivers of systemic risk. For example, the standard proxy for a financial institution's interconnectedness might not capture the risk concentrations caused by risky securitized assets at banks as seen during the financial crisis.

As our second main finding, we show that regulators only seem to care about an institution's size proxied by its total assets in their decision to declare the institution global systemically important. We find some correlation between the probability of being a G-SIFI and G-SII, and the institution's MES (banks) and ΔCoVaR (insurers). Nevertheless these proxies of systemic risk cannot explain the classification by regulators as soon as size is included in our probit regressions. We thus conclude that despite the methodologies published by regulators themselves, the decision to include a bank in the G-SIFI list was purely a question of bank size. Global systemically important insurers are clearly identifiable by a simple look at the total assets in their balance sheet.

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A Appendix

Table A.1: Sample insurers.

The table shows the names of the 98 international insurers used in our study. Insurers were selected by their respective total assets at the end of the fiscal year 2006 and availability of stock price data from *Datastream*.

ACE LIMITED	LOEWS CORPORATION
AEGON N.V.	MANULIFE FINANCIAL CORPORATION
AFLAC INCORPORATED	MAPFRE SA
AGEAS SA	MARSH & MCLENNAN COMPANIES, INC.
AIOI INSURANCE COMPANY LIMITED	MBIA INC.
ALLEANZA ASSICURAZIONI S.P.A.	MEDIOLANUM S.P.A
ALLIANZ LEBENSVERSICHERUNG-AG	METLIFE, INC.
ALLIANZ SE	MS & AD INSURANCE GROUP HOLDINGS, INCORPORATED
ALLSTATE CORPORATION (THE)	MUENCHENER RUCKVERSICHERUNGS-GESELLSCHAFT AG
AMBAC FINANCIAL GROUP, INC.	NATIONWIDE FINANCIAL SERVICES INC
AMERICAN FINANCIAL GROUP, INC.	NIPPONKOA INSURANCE COMPANY LIMITED
AMERICAN INTERNATIONAL GROUP, INC.	NUERNBERGER BETEILIGUNGS-AG
AMERICAN NATIONAL INSURANCE COMPANY	OLD MUTUAL PLC
AMP LIMITED	PERMANENT TSB GROUP HOLDINGS PLC
AON PLC	PHOENIX COMPANIES INC
ASSICURAZIONI GENERALI SPA	PING AN INSURANCE (GROUP) COMPANY OF CHINA LTD
ASSURANCES GENERALES DE FRANCE (AGF) SA	POWER CORPORATION OF CANADA
ASSURANT, INC.	POWER FINANCIAL CORP
AVIVA PLC	PREMAFIN FINANZIARIA SPA
AXA ASIA PACIFIC HOLDINGS LIMITED	PRINCIPAL FINANCIAL GROUP, INCORPORATED
AXA KONZERN AG	PROGRESSIVE CORPORATION (THE)
AXA LEBENSVERSICHERUNG AG	PROTECTIVE LIFE CORPORATION
AXA SA	PRUCO LIFE INSURANCE COMPANY
BALOISE HOLDING AG	PRUDENTIAL FINANCIAL, INCORPORATED
CATHAY FINANCIAL HOLDING COMPANY LIMITED	PRUDENTIAL PLC
CATTOLICA ASSICURAZIONI S.C.A.R.L.	QBE INSURANCE GROUP LIMITED
CHALLENGER FINANCIAL SERVICES GROUP LTD	REINSURANCE GROUP OF AMERICA, INC.
CHINA LIFE INSURANCE CO LTD	RSA INSURANCE GROUP PLC
CHUBB CORPORATION (THE)	SAMPO OYJ
CNA FINANCIAL CORPORATION	SANLAM LIMITED
CNO FINANCIAL GROUP, INCORPORATION	SCOR SE
CNP ASSURANCES	SHIN KONG FINANCIAL HOLDING COMPANY LIMITED
DBV-WINTERTHUR HOLDING AG	SOMPO JAPAN INSURANCE INC
ERGO VERSICHERUNGSGRUPPE AG	ST. JAMES'S PLACE PLC
FAIRFAX FINANCIAL HOLDINGS LIMITED	STOREBRAND ASA
FUBON FINANCIAL HOLDING COMPANY LIMITED	SUN LIFE FINANCIAL INCORPORATED
GENERALI DEUTSCHLAND HOLDING AG	SWISS LIFE HOLDING AG
GENWORTH FINANCIAL, INC.	SWISS RE LTD
GREAT EASTERN HOLDINGS LTD	TOKIO MARINE HOLDINGS INCORPORATED
GREAT-WEST LIFECO INC	TRAVELERS COMPANIES, INC. (THE)
HANNOVER RUECK SE	UNIPOL GRUPPO FINANZIARIO SPA
HARTFORD FINANCIAL SERVICES GROUP, INC. (THE)	UNIPOLSAI ASSICURAZIONI SPA
HELVETIA HOLDING AG	UNIQA INSURANCE GROUP AG
INDUSTRIAL ALLIANCE INSURANCE AND FINANCIAL SERVICES INCORPORATED	UNUM GROUP
ING GROEP N.V.	VIENNA INSURANCE GROUP
LEGAL & GENERAL GROUP PLC	WHITE MOUNTAINS INSURANCE GROUP LTD
LIBERTY GROUP LIMITED	WURTTEMBERGISCHE LEBENSVERSICHERUNG AG
LIBERTY HOLDINGS LIMITED	XL GROUP PLC
LINCOLN NATIONAL CORPORATION	ZURICH INSURANCE GROUP LIMITED

Table A.2: Sample banks.

The table shows the names of the 148 international banks used in our study. Banks were selected by their respective total assets at the end of the fiscal year 2006 and availability of stock price data from *Datastream*.

ABN AMRO HOLDING N.V.
ALLIANCE & LEICESTER PLC
ALLIED IRISH BANKS PLC
ALPHA BANK SA
AMERIPRISE FINANCIAL, INC.
ANGLO IRISH BANK CORPORATION PLC
AUSTRALIA AND NEW ZEALAND BANKING GROUP LIMITED
BANCO BILBAO VIZCAYA ARGENTARIA SA
BANCO COMERCIAL PORTUGUES, S.A.
BANCO DO BRASIL SA
BANCO ESPANOL DE CREDITO, S.A.
BANCO ESPIRITO SANTO SA
BANCO POPOLARE
BANCO POPULAR ESPANOL
BANCO SABADELL
BANCO SANTANDER SA
BANK AUSTRIA CREDITANSTALT AG
BANK HAPOALIM B.M.
BANK LEUMI LE-ISRAEL B.M.
BANK OF AMERICA CORPORATION
BANK OF CHINA LIMITED
BANK OF COMMUNICATIONS CO LTD
BANK OF IRELAND
BANK OF MONTREAL
BANK OF NEW YORK MELLON CORP.
BANK OF NOVA SCOTIA (THE)
BANK OF YOKOHAMA LIMITED (THE)
BANQUE NATIONALE DE BELGIQUE
BARCLAYS AFRICA GROUP LTD
BARCLAYS PLC
BAYERISCHE HYPO- UND VEREINSBANK AG
BB & T CORPORATION
BNP PARIBAS SA
BRADFORD & BINGLEY PLC
CANADIAN IMPERIAL BANK OF COMMERCE
CAPITAL ONE FINANCIAL CORPORATION
CAPITALIA SPA
CHIBA BANK LTD (THE)
CHINA CITIC BANK CORPORATION LIMITED
CHINA CONSTRUCTION BANK CORP
CHINA MERCHANTS BANK CO LTD
CHINA MINSHENG BANKING CORPORATION LIMITED
CITIGROUP INC.
COMERICA INCORPORATED
COMMERZBANK AKTIENGESELLSCHAFT
CREDIT AGRICOLE SA
CREDIT INDUSTRIEL ET COMMERCIAL SA
CREDIT SUISSE GROUP AG
DAIWA SECURITIES GROUP INCORPORATED
DANSKE BANK AS
DBS GROUP HOLDINGS LTD
DEPFA BANK PLC
DEUTSCHE BANK AKTIENGESELLSCHAFT
DEUTSCHE BOERSE AG
DEUTSCHE POSTBANK AG
DEXIA SA
DNB ASA
ECOBANK NIGERIA PLC
ERSTE GROUP BANK AG
ESPIRITO SANTO FINANCIAL GROUP S.A.
EUROBANK ERGASIAS SA
FIFTH THIRD BANCORP
FIRSTRAND LIMITED
GOLDMAN SACHS GROUP INC
HANA FINANCIAL GROUP
HANG SENG BANK LIMITED
HBOS PLC
HSBC HOLDINGS PLC
HUA XIA BANK COMPANY LTD
HYPO REAL ESTATE HOLDING
HYPOTHEKENBANK FRANKFURT AG
ICAP PLC
ICICI BANK LIMITED
INDUSTRIAL AND COMMERCIAL BANK OF CHINA LTD
INDUSTRIAL BANK CO LTD
INDUSTRIAL BANK OF KOREA
INTESA SANPAOLO SPA
JAPAN SECURITIES FINANCE CO LTD
JOYO BANK LIMITED (THE)
JPMORGAN CHASE & CO.
KAUPTHING BANK HF
KB FINANCIAL GROUP INCORPORATION
KBC GROUP NV
KEYCORP
KOREA EXCHANGE BANK
LANDESBANK BERLIN HOLDING AG
LLOYDS BANKING GROUP PLC
M & T BANK CORPORATION
MACQUARIE GROUP LIMITED
MALAYAN BANKING BERHAD
MARSHALL & ILSLEY CORPORATION
MEGA FINANCIAL HOLDING COMPANY LIMITED
MITSUBISHI UFJ FINANCIAL GROUP INCORPORATED
MIZUHO FINANCIAL GROUP INC
MORGAN STANLEY
NATIONAL AUSTRALIA BANK LIMITED
NATIONAL BANK OF CANADA
NATIONAL BANK OF GREECE, S.A.

Table A.2: Sample banks (continued).

NATIONAL CITY CORPORATION
NATIXIS
NIKKO CORDIAL CORPORATION
NISHI-NIPPON CITY BANK LIMITED (THE)
NOMURA HOLDINGS INCORPORATED
NORDEA BANK AB
NORTHERN ROCK PLC
NORTHERN TRUST CORPORATION
OSTERREICHISCHE VOLKSBANKEN - AG
OVERSEA-CHINESE BANKING CORPORATION LIMITED
PNC FINANCIAL SERVICES GROUP INCORPORATED
RAIFFEISEN BANK INTERNATIONAL AG
REGIONS FINANCIAL CORPORATION
RESONA HOLDINGS INC
ROYAL BANK OF CANADA
ROYAL BANK OF SCOTLAND GROUP PLC (THE)
SAN PAOLO IMI SPA
SBERBANK ROSSII OAO
SCHWEIZERISCHE NATIONALBANK
SHANGHAI PUDONG DEVELOPMENT BANK
SHINHAN FINANCIAL GROUP COMPANY LIMITED
SHINSEI BANK LIMITED
SHIZUOKA BANK LTD (THE)
SKANDINAVISKA ENSKILDA BANKEN
SLM CORPORATION
SOCIETE GENERALE
SOVEREIGN BANCORP INCORPORATED
ST. GEORGE BANK LIMITED
STANDARD BANK GROUP LIMITED
STANDARD CHARTERED PLC
STATE BANK OF INDIA
STATE STREET CORPORATION
SUMITOMO MITSUI FINANCIAL GROUP INC
SUMITOMO TRUST AND BANKING COMPANY LIMITED (THE)
SUNTRUST BANKS, INC.
SVENSKA HANDELSBANKEN AB
SWEDBANK AB
TAISHIN FINANCIAL HOLDING COMPANY LIMITED
TAIWAN COOPERATIVE BANK
TORONTO-DOMINION BANK (THE)
TURKIYE IS BANKASI A.S.
U.S. BANCORP
UBI BANCA
UBS AG
UNICREDIT SPA
UNITED OVERSEAS BANK LIMITED
WACHOVIA CORPORATION
WELLS FARGO & COMPANY
WESTPAC BANKING CORPORATION
WOORI FINANCE HOLDINGS

Table A.1: Variable definitions and data sources.

The appendix presents data sources, definitions and expected signs in our regression analyses for all dependent and independent variables that are used in the empirical study. The expected sign of each independent variable on the systemic risk of a bank or insurer is shown in the last column with a “+” indicating an expected increasing (and a “-” a decreasing) impact on systemic risk. The bank and insurer controls were taken from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	Definition	Data source	Hypotheses	Expected sign
Panel A: Systemic risk measures				
ΔCoVaR	Unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2014), measured as the difference of the Value-at-risk (VaR) of a financial sector index conditional on the distress of a particular insurer and the VaR of the sector index conditional on the median state of the firm.	Datastream, own calc.		
MES	Marginal Expected Shortfall as defined by Acharya et al. (2010) as the negative average return on an individual firm’s stock on the days the *MSCI World* index experienced its 5% worst outcomes.	Datastream, own calc.		
Panel B: Main independent variables				
Interconnectedness	PCAS measure as defined in Billio et al. (2012). PCAS is constructed using a decomposition of the variance-covariance matrix of the firms’ daily, standardized stock returns.	Datastream, own calc.	More exposure to other banks and insurers.	+
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210, WC03501)	Greater charter value incentivizes bank managers to keep their bank’s capital ratio and to limit their risk-taking (see Keeley, 1990 and Fahlenbrach et al. (2012)).	-
Total assets	Natural logarithm of a firm’s total assets.	Worldscope (WC02999)	Too-big-to-fail vs. more diversification.	+/-
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity.	Worldscope (WC02999, WC03501, WC08001), own calc.	Disciplining effect of leverage vs. greater vulnerability during financial crises (see Adrian and Shin, 2010).	+/-
Performance	Annual buy-and-hold stock returns computed from the first and last trading day in the year 2006.	Datastream, own calc.	Firms that performed well in the past will continue to perform well over time VS. institutions that took on too many risks in the past could also stick to their culture of risk-taking (see Fahlenbrach et al., 2012) and increase their exposure and contribution to systemic risk.	+/-
Return on assets	Return of the firm on it’s total assets after taxes (in %).	Worldscope (WC08326).	Higher profits can shield banks from the adverse effects of a financial crisis	-
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251, WC03255).	A less fragile funding structure of a bank makes it less vulnerable to sudden shortages in liquidity during a crisis (see Brunnermeier and Pedersen, 2009).	-

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

Variable name	Definition	Data source	Hypotheses	Expected sign
Panel C: Bank characteristics				
Deposits	Total deposits divided by total liabilities.	Worldscope (WC03019, WC03351).	Banks with more deposit financing are more stable in times of crises.	-
Loan loss provisions	Natural logarithm of expenses set aside as an allowance for uncollectable or troubled loans.	Worldscope (WC01271).	A larger buffer against troubled loans should serve as a stabilizing factor reducing a bank's total risk.	-
Loans	Ratio of total loans to total assets.	Worldscope (WC02271, WC02999).	A higher loans-to-assets ratio of a bank could indicate a business model that focuses on lending rather than more risky activities.	-
Tier-1-capital	Ratio of a bank's Tier-1-Capital to total assets.	Worldscope (WC18228, WC02999).	Higher regulatory bank capital acts as a buffer against losses and should stabilize both an individual bank and the financial sector.	-
Non-interest income	Non-interest income divided by total interest income.	Worldscope (WC01021, WC01016).	Higher values of non-interest income relative to total interest income could be indicative of a business model that concentrates more on non-deposit taking activities (like, e.g., investment banking) and thus more risk-taking (see, e.g., Brunnermeier et al., 2012).	+
Panel D: Insurer characteristics				
Investment success	Ratio of insurer's investment income to net revenues.	Worldscope (WC01001, WC01006), own calc.	Insurers become more intertwined with financial markets through asset management.	+
Loss ratio	Ratio of claim and loss expenses plus long term insurance reserves to earned premiums.	Worldscope (WC15549).	High loss ratio indicates bad quality of the insurance portfolio and increases default risk.	+
Non-Policyholder Liabilities	Total on balance sheet liabilities divided by total insurance reserves.	Worldscope (WC03351, WC03030).	Non-core insurance activities increase the risk to suffer from other sources in the financial market (see IAIS, 2013).	+
Operating expenses	Ratio of operating expenses to total assets.	Worldscope (WC01249, WC02999).	Poor management reflects the total risk of the insurance company.	+
Other income	Other pre-tax income and expenses besides operating income.	Worldscope (WC01262).	Non-core insurance activities increase the risk to suffer from other sources in the financial market (see IAIS, 2013).	+
Fixed income	Natural logarithm of fixed income.	Worldscope (WC01262).	Engagement in other asset classes than fixed income could suffer more profoundly from plummeting asset prices.	-

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Tables

Table I: Geographic sample distribution

The table shows the geographic spread for the sample of the largest 148 banks and for the 98 largest international insurers. The minimum and maximum values for the total assets in 2006 are given in billion US$.

	Banks			Insurer		
Country	Number	Min	Max	Number	Min	Max
AT	4	65.81	213.96	2	25.86	26.98
AU	5	77.73	453.41	4	19.04	72.99
BE	3	97.64	667.95	1	979.41	979.41
BM	-	-	-	1	19.55	19.55
BR	1	123.21	123.21	-	-	-
CA	6	99.94	458.57	7	19.48	326.43
CH	3	84.34	1815.56	6	25.1	327.94
CN	10	56.62	930.42	2	61.96	96.71
DE	8	76.7	1324.18	11	24.24	1311.58
DK	1	433.14	433.14	-	-	-
ES	5	85.01	972.82	1	28.07	28.07
FI	-	-	-	1	58.96	58.96
FR	5	252.57	1697.21	4	20.38	907.91
GB	10	77.85	1841.03	7	22.03	527.71
GR	3	58.42	90.01	-	-	-
HK	1	86.29	86.29	-	-	-
IE	4	86.41	262.94	2	59.49	94.49
IL	2	61.37	62.59	-	-	-
IN	2	61.48	154.75	-	-	-
IS	1	64.03	64.03	-	-	-
IT	6	80.59	963.16	7	23.68	454.27
JP	15	58.02	1578.76	5	26.12	143.65
KR	6	70.71	209.69	-	-	-
LU	1	72.85	72.85	-	-	-
MY	1	59.01	59.01	-	-	-
NG	1	130.39	130.39	-	-	-
NL	1	1160.22	1160.22	2	404.42	1318.22
NO	1	194.97	194.97	1	33.67	33.67
PT	2	69.66	92.84	-	-	-
RU	1	120.62	120.62	-	-	-
SE	4	170	393.23	-	-	-
SG	3	90.91	118.69	1	25.83	25.83
TR	1	63.15	63.15	-	-	-
TW	3	68.09	72.33	3	44.97	107.62
US	25	56.62	1841.03	27	17.91	985.44
ZA	3	78.04	152.69	3	29.89	51.96

Table II: Descriptive statistics: banks and insurers

The table shows summary statistics for the sample of the largest 148 banks and for the 98 largest international insurers. The values for the systemic risk measures MES and ΔCoVaR are given for the crisis period (July 2007 to December 2008) and the values for the three independent variables are calculated for the fiscal year 2006. Variable definitions and data sources are documented in Appendix A.1. All data are winsorized at the 1% and 99% levels.

					Banks				
	No. Obs.	Min.	10%	25%	Median	Mean	75%	90%	Max.
MES	148	-0.166	-0.048	0.001	0.033	0.025	0.064	0.097	0.137
ΔCoVaR	148	-0.021	-0.015	-0.010	-0.001	-0.005	0.000	0.000	0.001
Total assets (in billions)	148	56.620	65.278	85.010	151.200	350.800	345.500	1046.447	1841.000
Leverage	146	4.071	5.221	6.585	9.046	13.430	14.110	22.114	96.060
Interconnectedness (in 10^{-9})	148	0.000	0.000	0.012	15950.000	108900.000	149556.000	328951.000	1211000.000

					Insurer				
	No. Obs.	Min.	10%	25%	Median	Mean	75%	90%	Max.
MES	98	0.009	0.020	0.034	0.051	0.056	0.073	0.098	0.150
ΔCoVaR	98	-0.021	-0.019	-0.018	-0.015	-0.015	-0.013	-0.011	-0.004
Total assets (in billions)	98	17.910	23.187	27.080	56.390	158.700	147.300	405.449	131.000
Leverage	98	1.729	3.322	5.273	7.309	9.285	11.350	17.265	42.260
Interconnectedness (in 10^{-9})	98	0.000	0.003	0.012	0.078	0.078	0.211	0.368	1.001

Table III: Cross-sectional regression of systemic risk of banks.

The table shows the OLS and quantile regression results using a sample of the 148 largest banks. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on MES are on the 95%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix A.1. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	0.0008			0.0022	0.0008			0.0034*
	(0.121)			(0.100)	(0.527)			(0.090)
Leverage		0.0000		0.0000		0.0000		-0.0006
		(0.529)		(0.986)		(0.914)		(0.178)
Interconnectedness (in millions)			0.0118***	0.0000**			0.0153	0.0061
			(0.001)	(0.049)			(0.410)	(0.259)
Performance				-0.0040				-0.0096*
				(0.176)				(0.082)
ROA				-0.0019				-0.0012
				(0.177)				(0.528)
Debt maturity				-0.0021				-0.0033
				(0.469)				(0.647)
Deposits				-0.0016				-0.0037
				(0.761)				(0.709)
Loan loss provision				-0.0016				-0.0031
				(0.346)				(0.283)
Loans				0.0048				-0.0036
				(0.371)				(0.839)
Tier-1-capital				0.0939				0.1515
				(0.175)				(0.115)
Non-interest income				-0.0024				-0.0074**
				(0.340)				(0.045)
No. Obs.	148	146	148	92	148	146	148	92
R^2	0.0169	0.0025	0.1360	0.3204	-	-	-	-
Pseudo R^2	-	-	-	-	0.0108	0.0012	0.1066	0.4826
χ^2	1.01	0.05	4.02	23.23	-	-	-	-
p-value	0.316	0.817	0.045	0.000	-	-	-	-

Table IV: Cross-sectional regression of systemic risk of banks.

The table shows the OLS and quantile regression results using a sample of the 148 largest banks. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on ΔCoVaR are on the 5%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix A.1. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	MES	MES	MES	MES	MES	MES	MES	MES
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	0.0042			0.0062	0.0071			0.0022
	(0.389)			(0.669)	(0.311)			(0.888)
Leverage		-0.0002		-0.0007		-0.0003		-0.0046
		(0.475)		(0.530)		(0.589)		(0.205)
Interconnectedness (in millions)			-0.1150**	-0.2070***			0.0192	-0.1920*
			(0.018)	(0.000)			(0.483)	(0.069)
Performance				-0.0030				-0.0267
				(0.889)				(0.385)
ROA				-0.0132				-0.0451**
				(0.196)				(0.027)
Debt maturity				0.0153				0.0382
				(0.592)				(0.462)
Deposits				-0.0422				-0.2903*
				(0.383)				(0.051)
Loan loss provision				0.0040				0.0254
				(0.844)				(0.333)
Loans				-0.0287				0.1026
				(0.704)				(0.197)
Tier-1-capital				0.5999				1.3814
				(0.196)				(0.173)
Non-interest income				-0.0122				-0.0283
				(0.567)				(0.281)
No. Obs.	148	146	148	92	148	146	148	92
R^2	0.0047	0.0028	0.1409	0.2975	-	-	-	-
Pseudo R^2	-	-	-	-	0.0212	0.0053	0.0003	0.2319
χ^2	5.71	0.02	34.21	0.14	-	-	-	-
p-value	0.017	0.895	0.000	0.713	-	-	-	-

Table V: Cross-sectional regression of systemic risk of insurers.

The table shows the OLS and quantile regression results using a sample of the 98 largest insurance companies. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on ΔCoVaR are on the 5%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix A.1. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	-0.0006*			-0.0009	0.0003			0.0007
	(0.082)			(0.408)	(0.367)			(0.237)
Leverage		0.0001*		0.0002**		0.0001		0.0002*
		(0.063)		(0.043)		(0.214)		(0.078)
Interconnectedness			0.0032*	0.0022			0.0021	0.0058*
			(0.089)	(0.468)			(0.344)	(0.087)
Performance				-0.0003				0.0006
				(0.873)				(0.743)
ROA				0.0006				0.0011***
				(0.237)				(0.000)
Debt maturity				0.0014				-0.0006
				(0.550)				(0.804)
Investment success				0.0064				0.0063
				(0.305)				(0.094)
Loss ratio				0.0000				0.0000**
				(0.651)				(0.015)
Non-policyholder liabilities				-0.0004				0.0000
				(0.283)				(0.974)
Operating expenses				-0.0124				-0.0036
				(0.111)				(0.353)
Other income				0.0000				0.0000
				(0.623)				(0.853)
Fixed income				0.0000				-0.0012**
				(0.999)				(0.025)
No. Obs.	98	98	98	71	98	98	98	71
R^2	0.0307	0.0307	0.0315	0.1973	-	-	-	-
Pseudo R^2	-	-	-	-	0.0092	0.0283	0.0332	0.3263
χ^2	0.01	0.37	0.40	0.75	-	-	-	-
p-value	0.909	0.544	0.53	0.385	-	-	-	-

Table VI: Cross-sectional regression of systemic risk of insurers.

The table shows the OLS and quantile regression results using a sample of the 98 largest insurance companies. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on MES are on the 95%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix A.1. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	MES	MES	MES	MES	MES	MES	MES	MES
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	0.0095***			0.0019	0.0111			-0.0106
	(0.000)			(0.806)	(0.269)			(0.442)
Leverage		-0.0006		-0.0009		-0.0009		-0.0013
		(0.131)		(0.204)		(0.752)		(0.575)
Interconnectedness			-0.0275**	0.0156			-0.0734	-0.0141
			(0.020)	(0.453)			(0.179)	(0.795)
Performance				-0.0390***				-0.0594**
				(0.001)				(0.012)
ROA				0.0024				-0.0018
				(0.551)				(0.805)
Debt maturity				0.0048				-0.0022
				(0.762)				(0.967)
Investment success				0.1042*				0.1318
				(0.063)				(0.199)
Loss ratio				-0.0001**				-0.0001
				(0.025)				(0.363)
Non-policyholder liabilities				0.0006				-0.0055
				(0.858)				(0.651)
Operating expenses				-0.0934				-0.1014
				(0.277)				(0.497)
Other income				0.0000				0.0000
				(0.422)				(0.691)
Fixed income				0.0077				0.0188
				(0.210)				(0.206)
No. Obs.	98	98	98	71	98	98	98	71
R^2	0.1128	0.0154	0.0339	0.4932	-	-	-	-
Pseudo R^2	-	-	-	-	0.0432	0.0098	0.0394	0.4905
χ^2	0.88	0.02	1.55	5.13	-	-	-	-
p-value	0.347	0.880	0.213	0.024	-	-	-	-

Table VII: Systemic relevance of banks: probit regressions.

The table shows the results of several probit regressions on a dummy variables that is one if a bank was nominated as global systemically important by the Financial Stability Board and zero otherwise. Our sample consists of the 148 largest banks measured by their total assets at the end of the fiscal year 2006. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. P-values are given in parentheses and ***,**,* denote statistical significance at the 1%,5% and 10% level. Definitions of variables as well as descriptions of the data sources are given in Table A.1 in the Appendix.

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Total assets)	1.5630***					1.5620***	1.8896***
	(0.000)					(0.000)	(0.000)
Leverage		0.0020				-0.0157	0.0336
		(0.811)				(0.574)	0.480
Interconnectedness			0.0000			0.0000	
			(0.939)			(0.743)	
MES				5.1186**		3.0310	3.4083
				(0.031)		(0.327)	(0.325)
ΔCoVaR					14.5811		
					(0.462)		
Market-to-book ratio							0.2961
							(0.532)
Performance							-0.0411
							(0.975)
ROA							0.4492
							(0.304)
Debt maturity							0.5344
							(0.685)
Deposits							0.9625
							(0.621)
Non-interest income							1.4046*
							(0.052)
Observations	146	144	146	146	146	141	108
AIC	55.43	140.74	141.57	136.36	141.02	59.68	55.14

Table VIII: Systemic relevance of insurers: probit regressions.

The table shows the results of several probit regressions on a dummy variables that is one if an insurer was nominated as global systemically important by the Financial Stability Board and zero otherwise. Our sample consists of the 98 largest insurers measured by their total assets at the end of the fiscal year 2006. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. P-values are given in parentheses and ***,**,* denote statistical significance at the 1%,5% and 10% level. Definitions of variables as well as descriptions of the data sources are given in Table A.1 in the Appendix.

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Log(Total assets)	0.9546***					1.526***
	(0.000)					(0.005)
Leverage		0.0287				-0.0760
		(0.188)				(0.482)
Interconnectedness			-0.1704			1.468
			(0.844)			(0.567)
MES				7.0939		
				(0.177)		
ΔCoVaR					-145.0350**	-64.3375
					(0.032)	(0.526)
Market-to-book ratio						-0.027
						(0.950)
Performance						1.9750
						(0.227)
ROA						-0.354
						(0.672)
Debt maturity						-0.3316
						(0.810)
Observations	96	96	96	96	96	96
AIC	37.95	62.67	64.08	62.51	58.28	41.86