Systemic Risk in Financial Markets:
How Systemically Important are Insurers?

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Abstract

We study how insurers contribute to systemic risk in financial markets. Systemic risk is measured as the market value of distressed losses to financial institutions' creditors, and in terms of tail interdependence between individual financial institutions and the broader financial system. The global financial system is represented by a panel of 183 major banks and insurers over the pre-crisis and crisis periods from January 2005 to December 2014. On the sector level, we find that the insurance sector generally contributes very little to the aggregate amount of systemic risk in the global financial system; during the financial crisis and the European sovereign debt crisis, its systemic risk share averaged only 9 percent. On the level of individual institutions, however, several multi-line and life insurers appear as systemically risky as the riskiest banks. Our results indicate that insurers' level of systemic risk varies by line of insurance, and provide a preliminary affirmation that some insurers are systemically important financial institutions. We discuss several important implications for the regulation of systemic risk in financial markets.

Keywords: financial crisis, European sovereign debt crisis, systemic risk, global systemically important insurer, distress insurance premium, credit default swap
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1. Introduction

Insurers experienced distress in the financial crisis; however, their status as systemically important financial institutions is disputed. During the financial crisis, insurance company American International Group (AIG) was brought to the brink of failure by severe losses in its financial markets businesses. The firm's ultimate rescue from bankruptcy illustrates that the default of an insurer may send such repercussions to the wider financial system as to provoke government interventions (Harrington, 2009). More recently, European life insurers appear prone to collective failure in a double-hit scenario of sustained low interest rates and a sudden drop in asset prices. Under this scenario, widespread loss of market confidence in financial institutions could easily occur (ESRB, 2015).

In the aftermath of the financial crisis, regulators set out to identify global systemically important financial institutions (G-SIFIs) to be subjected to closer regulatory scrutiny.[1] As part of this general initiative, the Financial Stability Board (FSB) and the International Association of Insurance Supervisors (IAIS) embarked on a joint effort to identify and regulate global systemically important insurers (G-SIIs). Based on an initial assessment methodology developed by the IAIS, a list of systemically important insurers was first published by the FSB in July 2013.[2] The identified insurers are subjected to a range of additional policy measures, including enhanced group-wide supervision, recovery and resolution planning requirements, and higher loss absorbency requirements.

While policy measures targeting systemically important insurers are now being phased in, there is still much controversy over whether the insurance sector poses a systemic risk, and if so, how this risk should be measured, and how systemically important insurers should be regulated. Industry representatives have argued that insurers enhance financial stability rather than posing a systemic risk (Kessler, 2014). Previous research has criticized the regulatory assessment methodology (Weiß and Mühlnickel, 2014; Bierth et al., 2015), and has argued that a systemic risk regulator for insurance companies would compromise market efficiency (Harrington, 2009). Meanwhile, the future status of individual insurers is uncertain, as MetLife has successfully challenged its systemic risk label in trial court.

As noted by the IAIS (2011), systemic risk in insurance ultimately needs to be judged on empirical grounds. Despite its pivotal role in the regulation of financial markets, however, empirical evidence on the subject remains surprisingly limited.

Against this background, we set out to contribute to a better informed regulation of systemic risk by an empirical assessment of systemic risk in insurance. We model the

[1] G-SIFIs are defined as "institutions of such size, market importance, and global interconnectedness that their distress or failure would cause significant dislocation in the global financial system and adverse economic consequences across a range of countries" (FSB, 2010, p. 2).

[2] This list is reviewed annually. The list of systemically important insurers published in July 2013 included Allianz, AIG, Assicurazioni Generali, Aviva, AXA, MetLife, Ping An, Prudential Financial, and Prudential. The November 2014 update left the G-SII list unchanged. In November 2015, Aegon replaced Assicurazioni Generali. Reinsurers were not included in the underlying assessments.

global insurance sector in the context of the global financial system and analyze systemic risk in insurance relative to systemic risk in banking. Our sample financial system is a panel of 183 financial institutions over the period from January 2005 to December 2014. The sample includes 133 banks and 50 insurers, accounting for almost half of the global banking and insurance assets, and almost all officially identified G-SIFIs. In our analysis, we address the following three main questions: First, what is the contribution of the insurance sector to the aggregate level of systemic risk in the global financial system? Second, how risky is the insurance sector compared to the banking sector? Finally, to what degree are individual insurers systemically important?

We set our analysis in the general modeling framework of Huang et al. (2009, 2012a,b). The financial system is represented by a portfolio of debts, and financial crises are modeled as severe portfolio losses. The aggregate systemic risk of the financial system is measured as the premium of a hypothetical insurance contract covering distressed losses to the financial institutions' creditors. The systemic importance of individual financial institutions is measured as their marginal contribution to aggregate systemic risk and in terms of tail interdependence between the individual institutions and the broader financial system. We conduct a forward-looking assessment of systemic risk estimating the risk measures from credit default swap (CDS) spreads.

As our main result, we point out an important ambiguity between the systemic risk posed by the insurance sector and the systemic importance of individual insurers. Indeed, the insurance sector contributes a relatively small share to the aggregate level of systemic risk in the global financial system, averaging only 9 percent over the period of the global financial crisis and the ensuing European sovereign debt crisis. The insurance sector overall also appears to be less risky than the banking sector on a relative basis. On the level of individual financial institutions, however, a number of multi-line and life insurers exhibit similar levels of systemic risk as the riskiest banks in our sample. Our results therefore indicate that some insurers are systemically important financial institutions.

In summary, we contribute to the literature on the empirical side and on the methodological side. On the empirical side, we document a rich set of stylized facts on systemic risk in insurance. We differentiate between life, non-life, and reinsurance, and study aggregate systemic risk contributions as well as individual systemic importance. To the best of our knowledge, our research provides the broadest cross-sectional study of financial institutions using CDS-implied systemic risk measures to date.

On the methodological side, we provide an extended framework for the assessment of systemic risk. Our implementation includes additional tail interdependence measures, and applies to listed as well as unlisted firms. We expect that including unlisted firms will reinforce the analyses of systemic risk in regional and domestic financial markets with a high share of such firms. It further allows us to analyze the systemic risk contribution of diversified financial holding companies operating both banking and insurance businesses more granularly at the subsidiary level.

The remainder of this paper proceeds as follows. Section 2 reviews the literature on systemic risk measurement and on systemic risk in insurance. Section 3 introduces the modeling framework. Section 4 describes the sample financial system and Section 5 discusses our empirical findings. Section 6 derives policy implications and recommendations. Section 7 provides concluding remarks.

2. Related Literature

We will review two interdependent streams of literature concerned with the measurement of systemic risk and the existence of systemic risk in insurance. Our work relates and contributes to both areas, as we will analyze systemic risk in insurance drawing on and extending empirical approaches for systemic risk measurement.

2.1. Measurement of Systemic Risk

Most work on systemic risk has taken an empirical perspective using market, financial statements, or exposure data. Empirical measures based on market data are forward-looking by nature since market data reflects market participants' aggregate expectations about future events. This contrasts with financial statements and exposure data, which are essentially the result of past financial transactions.

Two main branches of empirical literature on systemic risk measurement have emerged. Contributions relating to the first branch analyze the degree of interconnection and the potential for contagion within the financial system based on statistical inference on market (Billio et al., 2012; Hautsch et al., 2014, 2015) or exposure data (van Lelyveld et al., 2011; Park and Xie, 2014). Contributions relating to the second branch analyze the time series of aggregate systemic risk and the cross section of individual systemic importance studying the distributional characteristics of some loss metric. This is the main interest of the present work, and we will therefore focus on the related literature below.

Systemic risk is in a way an elusive concept as illustrated by the lack of a universal definition in the empirical literature to date. Financial crises have been defined, and systemic risk has been measured, in terms of financial returns, capital shortfall, and default losses. Contributions concerned with the individual systemic importance of financial institutions have taken different perspectives and have measured systemic importance in terms of institutions' *contribution* to financial instability, and in terms of institutions' *exposure* to turmoil in the broader financial system.

Adrian and Brunnermeier (2016) measure the contribution of financial institutions to systemic risk based on their tail interdependence with the financial system. They propose the CoVaR measure, defined as the value at risk of the financial system return conditional on a particular return level of a financial institution. The systemic importance of the institution is then measured as the increase in CoVaR as the institution moves from its median state to a state of distress. Acharya et al. (2010) measure the exposure of financial institutions to financial crises based on the marginal expected shortfall (MES), which they define as an institution's return conditional on a downturn of the entire financial system.

Brownlees and Engle (2015) and Huang et al. (2009) model the financial system as a portfolio where each financial institution represents a particular exposure. Within this setting, Brownlees and Engle (2015) define financial crises as a sufficiently adverse portfolio return. Aggregate systemic risk is then measured by SRISK, defined as the aggregate capital shortfall of the portfolio in times of crisis. The marginal contribution of each institution to aggregate systemic risk corresponds to its individual capital shortfall.

Huang et al. (2009) define financial crises as a situation where a large share of the portfolio liabilities is in default. Aggregate systemic risk is then measured by the distress insurance premium (DIP), defined as the premium of a hypothetical insurance contract covering the aggregate loss induced by a financial crisis. Huang et al. (2012a,b) later extend this framework and measure the marginal contribution of each institution to aggregate systemic risk as the premium required to cover individual losses in a financial crisis.

Several portfolio-based approaches related to these frameworks have been proposed. Malz (2013) considers a similar systemic event condition as Brownlees and Engle (2015), but measures the systemic importance of financial institutions using probability-based measures of tail interdependence: the conditional probability that a firm defaults in a financial crisis, measuring the exposure of the firm and the probability of a financial crisis if a firm is in distress, measuring its contribution. Puzanova and Düllmann (2013) consider losses in portfolio liabilities using a framework similar to the one of Huang et al. (2009, 2012a,b), but define financial crises in terms of a probability level of the portfolio loss distribution rather than in terms of a loss threshold. Aggregate systemic risk of the portfolio is then measured as the expected shortfall, and the marginal contribution of a financial institution is measured as its expected default loss in a financial crisis.

We set our analysis in the general modeling framework of Huang et al. (2009, 2012a,b). This framework has been applied to study systemic risk in regional and global banking systems (Huang et al., 2009, 2012a,b; Lahmann and Kaserer, 2011; Black et al., 2016), and has recently been adopted to analyze contagion between the banking and insurance sectors (Chen et al., 2014). The underlying implementations sample correlated defaults of financial institutions from structural models of portfolio credit risk and infer the underpinning credit risk parameters from CDS and equity market data.

Our implementation extends this modeling framework in two key dimensions. First, we estimate the credit risk parameters using only CDS spreads. Opposed to the previous DIP literature, we do not require additional equity data. Our implementation is therefore applicable to both listed and unlisted firms. This is of advantage in financial systems with a high share of unlisted savings and co-operative institutions, and further allows analyzing financial holding companies such as bancassurances at the subsidiary level. Second, we consider a broader set of risk measures. We implement the aggregate and marginal DIP measures of Huang et al. (2009, 2012a,b), and additionally tail interdependence measures similar to those considered by Malz (2013). This enables us to capture the multifaceted nature of systemic risk in a coherent framework.

2.2. Systemic Risk in Insurance

Systemic risk in insurance has been studied even before the financial crisis; however, empirical contributions on the subject remain limited. Trichet (2005) provides a pre-crisis treatment of the role of insurance for financial stability. While insurance was traditionally only marginally associated with systemic risk, he argues that ongoing convergence of the banking and insurance business models as well as growing interconnectedness between the banking and insurance sectors can create new sources of systemic risk.

In the post-crisis literature, Baluch et al. (2011) and Cummins and Weiss (2014) follow a similar line of argument and find that the interlinkages between the banking sector and the insurance sector have increased in recent years. Systemic risk in insurance is mainly attributed to non-traditional and non-insurance activities such as financial guarantee insurance and derivatives trading, which exposes insurers to contagion from banks. This view is reinforced by Acharya and Richardson (2014), who argue that the insurance sector may pose a systemic risk as the industry is no longer traditional but has become more interconnected in financial markets and more prone to runs.

Chen et al. (2014) conduct an empirical assessment of the interconnectedness between banks and insurers. They measure the time series of systemic risk in the banking sector and the insurance sector using the DIP indicator of Huang et al. (2009). Their results indicate that the aggregate level of systemic risk in the insurance sector is contained compared to the banking sector, and provide evidence that the impact of distress in the banking sector on the insurance sector is stronger and more persistent than in the other direction.

The initial assessment approach for G-SIIs proposed by the IAIS is based on a set of indicators measuring the size, global activity, interconnectedness, non-traditional and non-insurance activities, and substitutability of insurance firms (IAIS, 2013). Weiß and Mühlnickel (2014) and Bierth et al. (2015) analyze the impact of firm characteristics relating to these categories on insurers' exposure and contribution to systemic risk. Their results only lend partial support to the regulatory assessment approach. Both studies use the CoVaR measure (Adrian and Brunnermeier, 2016), the MES measure (Acharya et al., 2010), and the SRISK measure (Brownlees and Engle, 2015) as dependent variables. Weiß and Mühlnickel (2014) analyze a panel of U.S. insurers for the period of the financial crisis. They conclude that size is a major driver of insurers' exposure and contribution to systemic risk. The exposure to systemic risk additionally depends on non-traditional and non-insurance activities, whereas factors related to the other regulatory assessment categories do not appear to be associated with systemic risk. Bierth et al. (2015) consider a panel of international insurers for the period of the financial crisis and the European sovereign debt crisis. They find that the interconnectedness of insurers within the insurance sector drives insurers' exposure to systemic risk. The contribution to systemic risk, however, appears to be mainly driven by leverage.

Reinsurers have not yet been subjected to regulatory assessment concerning a potential status as G-SIFIs, and their role with respect to systemic risk is actively debated in the literature. Cummins and Weiss (2014) argue that both property-casualty (P/C) insurers and life insurers are potentially prone to reinsurance failures as the default of reinsurance exposures may impair their solvency. Van Lelyveld et al. (2011) and Park and Xie (2014) conduct empirical assessments using exposure-based models and find the risk of insurance sector crises triggered by reinsurance failures to be rather contained.

Reviewing this literature, the recent work by Chen et al. (2014) is closest to ours. There are, however, a number of important differences between the analyses contained therein and our work. Foremost, Chen et al. (2014) focus on the interconnection between the banking and the insurance sector. They are particularly concerned with the potential of contagion between the two sectors. Our main interest centers on the level of systemic risk associated with the insurance sector in general and different types of insurance in particular. We separately analyze systemic risk in life, non-life, and reinsurance lines. Given the focus of their analysis, Chen et al. (2014) consider the time series of aggregate systemic risk in the banking and insurance sector. We additionally consider the cross section of systemic risk associated with individual insurers in the context of a sample global financial system. While previous research indicates that the aggregate level of systemic risk in insurance is lower than in banking, selected insurance firms may still be systemically important. Finally, Chen et al. (2014) base their analysis on a panel of U.S.-listed insurance and banking firms, which covers the early stages of the financial crisis up to May 2008. We conduct an extended analysis with global scope, which covers the full financial crisis and the European sovereign debt crisis.

3. Modeling Framework

We define and analyze systemic risk in terms of losses in the liabilities of the financial system. We derive these losses setting the financial system in the general framework of a portfolio credit risk model. This section introduces our modeling framework.

We first derive the portfolio credit risk model and define financial crises as a major loss event. Starting from this definition, we then implement measures for the time series of aggregate systemic risk and the cross section of individual systemic importance. In a last step, we estimate the underlying credit risk parameters from market data.

3.1. Modeling Systemic Events

We represent the financial system as a portfolio of financial firms' debts. The portfolio weight of each firm is given by the book value of its total liabilities. The portfolio realizes a loss if and only if one or more firms are in default at the end of the period of interest.

As in the Merton (1974) model, individual firms default if their asset value falls short of a minimum solvency requirement. Interdependence among individual firms is introduced by common exposures driving the firms' asset returns. Given sufficiently severe losses to the debt holders, a financial crisis occurs.[3] We set out the portfolio credit risk model and the condition for a financial crisis in more formal terms below.[4]

Let us denote the financial system by a set of firms $\mathcal{S} = \{1, \ldots, N\}$. Each firm i has total assets with a time t market value of $A_{i,t}$ and total liabilities with a book value of X_i. The standardized h-period asset return of firm i is given by the multifactor model

$$R_{i,t:t+h} = F_i \, Y_{t,t+h} + \sqrt{1 - F_i F_i^{\top}} \, Z_{i,t,t+h}. \tag{3.1}$$

$Y_{t,t+h} = \left[Y_{1,t,t+h}, \ldots, Y_{M,t,t+h}\right]^{\top}$ represents M common factors, $Z_{i,t,t+h}$ is an idiosyncratic factor specific to firm i, and $F_i = [F_{i,1}, \ldots, F_{i,M}]$, $F_i F_i^{\top} \leq 1$, are the common factor loadings. All factors are assumed to be mutually independent and standard normally distributed. The asset returns are therefore standard normally distributed and, for $i \neq j$, correlated by $\rho_{ij} = \operatorname{corr}\left(R_{i,t:t+h}, R_{j,t:t+h}\right) = F_i F_j^{\top}$.

Firm i will default h periods into the future if its asset value at time $t + h$ misses a minimum solvency requirement given by the default point D_i. This has probability

$$\begin{aligned} PD_{i,t}\left(h; D_i\right) &= \mathrm{P}\left(A_{i,t+h} < D_i \mid A_{i,t}\right) && (3.2) \\ &= \mathrm{P}\left(R_{i,t:t+h} < -DTD_{i,t}\left(h; D_i\right) \mid A_{i,t}\right) && (3.3) \\ &= \Phi\left(-DTD_{i,t}\left(h; D_i\right)\right), && (3.4) \end{aligned}$$

where $DTD_{i,t}\left(h; D_i\right)$, the distance-to-default, is a measure of firm i's credit quality over the next h periods, and Φ is the standard normal distribution function.

Let $RR_{i,t+h} \in [0, 1]$ denote the average recovery rate of the liabilities owed by firm i.[5] Conditional on default of the firm, the portfolio incurs a marginal loss of $(1 - RR_{i,t+h}) \cdot X_i$. The portfolio credit risk model for default of individual firms, indicated by $I_{i,t+h}$, the loss incurred by individual firms, measured by $L_{i,t+h}$, and the aggregate loss incurred by the

[3] In practice, some debt holders will be partly or fully protected against losses by deposit insurance schemes, guarantee funds, or other types of guarantees. Our analysis does not depend on the ultimate loss bearer. We will therefore assume that losses are directly incurred by the debt holders throughout.

[4] The resulting portfolio credit risk model corresponds to the normal copula model for portfolio credit risk. It is widely used in practical credit risk applications; see, e.g., Glasserman and Li (2005).

[5] We assume that the recovery rate is independent of the default probability.

financial system, measured by $L_{\mathcal{S},t+h}$, can now be stated as follows:

$$I_{i,t+h} = \mathbf{1}_{\left\{R_{i,t:t+h} < -DTD_{i,t}(h;D_i)\right\}}, \tag{3.5}$$

$$L_{i,t+h} = (1 - RR_{i,t+h}) \cdot X_i \cdot I_{i,t+h}, \tag{3.6}$$

$$L_{\mathcal{S},t+h} = \sum_{i \in \mathcal{S}} L_{i,t+h}. \tag{3.7}$$

We define $\mathbf{1}_{\{x\}} = 1$ if condition x is true and 0 otherwise.

Within this framework, we define a financial crisis as a major loss event. We define this event in terms of a loss threshold for its severity, as in Huang et al. (2009) and Brownlees and Engle (2015), rather than in terms of a probability threshold for its occurrence, as in Puzanova and Düllmann (2013) and Adrian and Brunnermeier (2016). Specifically, we consider a loss in aggregate liabilities exceeding a given threshold of the portfolio size. We will refer to such a loss as a *systemic event*. The systemic event condition writes:

$$\sum_{i \in \mathcal{S}} L_{i,t+h} = L_{\mathcal{S},t+h} > SLT = SLT^{rel} \cdot \sum_{i \in \mathcal{S}} X_i. \tag{3.8}$$

The systemic loss threshold defines the loss to be exceeded to trigger a systemic event. In the systemic event condition it is given by SLT in absolute units of currency, and by $SLT^{rel} \in (0, 1]$ as a sufficiently large share of total liabilities in the financial system.

3.2. Measuring Systemic Risk

We measure systemic risk from different perspectives. We first implement the DIP measures originally proposed by Huang et al. (2009, 2012a,b), and recently applied by Lahmann and Kaserer (2011), Chen et al. (2014), and Black et al. (2016). These measure aggregate systemic risk and financial institutions' marginal contributions as the market value of losses in a systemic event. We further implement measures of tail interdependence between the broader financial system and individual financial institutions as suggested by Malz (2013). These measure the propensity of an individual institution to be distressed if the financial system experiences a systemic event, and vice versa.

All risk measures are implemented using Monte Carlo methods. Since systemic events constitute major loss events that are rarely observed, plain Monte Carlo methods may be slow to converge. To enhance the efficiency and precision of our systemic risk metrics, we implement an importance sampling procedure.[6] Following Glasserman and Li (2005) and Glasserman (2005), we apply a mean-shift to the distribution of the common factors underpinning the asset returns.

[6]Importance sampling is a statistical tool to reduce the variance of Monte Carlo estimators. Its basic principle is to change the original probability measure so that the events of interest occur more often in the simulation. The Monte Carlo estimator is de-biased for the change of measure using a likelihood ratio.

3.2.1. Distress Insurance Premium

Intuitively, the DIP measures aggregate systemic risk as the premium of a hypothetical insurance policy covering distressed losses of the financial system (Huang et al., 2009); hence its name. Technically, this premium is given by the market value of a contingent claim paying the aggregate losses in liabilities if a systemic event occurs at maturity and nothing otherwise. Following this approach, the time t assessment of the aggregate level of systemic risk over the next h periods is given by

$$\begin{aligned} DIP_{\mathcal{S},t}\left(h\right) &= \mathrm{E}^{Q}\left(L_{\mathcal{S},t+h}\cdot\mathbf{1}_{\left\{L_{\mathcal{S},t+h}>SLT\right\}}\right)\cdot e^{-rh} \\ &= \underbrace{\mathrm{P}^{Q}\left(L_{\mathcal{S},t+h}>SLT\right)}_{PSD}\cdot\underbrace{\mathrm{E}^{Q}\left(L_{\mathcal{S},t+h}\mid L_{\mathcal{S},t+h}>SLT\right)}_{ETL}\cdot e^{-rh}. \end{aligned} \tag{3.9}$$

r is the risk-free rate. The expectation and probability are under the risk-neutral measure. PSD defines the risk-neutral probability of systemic distress (PSD), and ETL defines the expected tail loss (ETL). The risk-neutral PSD incorporates the physical probability of a systemic event and a risk premium component. The ETL as defined here is closely related to the expected shortfall encountered in financial risk management. Both measure the expected loss of a portfolio under extreme conditions. The subtle difference resides in the fact that the ETL is defined conditional on a loss threshold, whereas the expected shortfall is defined in terms of a probability threshold. We note that the risk-neutral PSD corresponds to the compounded premium required for one unit of ETL.

The aggregate systemic risk of the financial system as measured above can be fully allocated to the individual financial institutions in the portfolio (Huang et al., 2012a,b). The marginal contribution of firm i to aggregate systemic risk is given by

$$\begin{aligned} DIP_{i,t}\left(h\right) &= \mathrm{E}^{Q}\left(L_{i,t+h}\cdot\mathbf{1}_{\left\{L_{\mathcal{S},t+h}>SLT\right\}}\right)\cdot e^{-rh} \\ &= \underbrace{\mathrm{P}^{Q}\left(L_{\mathcal{S},t+h}>SLT\right)}_{PSD}\cdot\underbrace{\mathrm{E}^{Q}\left(L_{i,t+h}\mid L_{\mathcal{S},t+h}>SLT\right)}_{METL_i}\cdot e^{-rh}, \end{aligned} \tag{3.10}$$

where $METL_i$ defines the firm's marginal ETL. We now can determine the marginal contribution $DIP_{\bar{\mathcal{S}},t}\left(h\right)$ of an arbitrary subportfolio $\bar{\mathcal{S}}\subseteq\mathcal{S}$ of the financial system aggregating the marginal contributions $DIP_{i,t}\left(h\right)$ of each firm $i\in\bar{\mathcal{S}}$,

$$DIP_{\bar{\mathcal{S}},t}\left(h\right)=\sum_{i\in\bar{\mathcal{S}}}DIP_{i,t}\left(h\right). \tag{3.11}$$

The systemic risk measures of Equations (3.9), (3.10), and (3.11) express systemic risk in currency units. The time series of systemic risk will therefore reflect changes in the liability size of the portfolio. To adjust for portfolio size, the risk measures alternatively can be expressed in relative terms as unit price per unit of portfolio size, $DIP^{unit}_{\bar{\mathcal{S}},t}\left(h\right)$, and as a share of total systemic risk, $DIP^{share}_{\bar{\mathcal{S}},t}(h)$:

$$DIP^{unit}_{\bar{\mathcal{S}},t}(h) = \frac{DIP_{\bar{\mathcal{S}},t}(h)}{\sum_{i \in \mathcal{S}} X_i}, \qquad DIP^{share}_{\bar{\mathcal{S}},t}(h) = \frac{DIP_{\bar{\mathcal{S}},t}(h)}{DIP_{\mathcal{S},t}(h)}, \tag{3.12}$$

where we define $DIP^{share}_{\bar{\mathcal{S}},t}(h)$ to be zero if $DIP_{\mathcal{S},t}(h)$ is zero.

3.2.2. Tail Interdependence Measures

We analyze interdependence between individual financial institutions and the broader financial system by means of two conditional tail probability measures. The measures differ by the direction of conditioning: the conditional probability of default (CoPD) conditions on distress at the level of the financial system and evaluates the outcome at the firm level. Reversing the conditioning, the conditional probability of systemic distress (CoPSD) conditions on distress at the firm level and evaluates the outcome at the level of the financial system. We define the CoPD associated with firm i as the risk-neutral probability of a default by the firm conditional on a systemic event,

$$CoPD_{i,t}(h) = \mathrm{P}^{Q}\left(R_{i,t:t+h} < -DTD_{i,t}(h; D_i) \mid L_{\mathcal{S},t+h} > SLT\right); \tag{3.13}$$

and the CoPSD associated with firm i as the risk-neutral probability of a systemic event conditional on the firm's asset return falling short of its q-quantile,[7]

$$CoPSD_{i,t}(h) = \mathrm{P}^{Q}\left(L_{\mathcal{S},t+h} > SLT \mid R_{i,t:t+h} < \Phi^{-1}(q)\right). \tag{3.14}$$

The two risk measures introduced above measure tail interdependence in the financial system from complementary perspectives. The CoPD measures the resilience of a firm in times of severe turmoil in the broader financial system. The CoPSD, on the other hand, measures the potentially destabilizing effect of a firm on the financial system as a whole. While neither measure aims at making *causal* inferences, they serve to identify firms for closer regulatory scrutiny based on the degree of *association*. In that sense, the CoPD relates to microprudential regulation. Regulatory measures targeting this risk measure will aim at limiting the potential for distress of an individual firm by shedding it against exogenous crises, with the ultimate goal of mitigating potential losses to the depositors, policyholders, and investors of the firm. The CoPSD relates to macroprudential regulation. Regulatory measures targeting this risk measure will aim at reducing the impact of distress of an individual firm on the broader financial system, with the ultimate goal of mitigating

[7] Note that we define CoPSD conditional on the q-quantile of the asset return distribution rather than conditional on firm default. Conditioning on the q-quantile ensures that the conditioning event has probability q across all financial firms by definition. Conditioning on firm default corresponds to conditioning on a firm-specific return level, and the probability of the conditioning event would therefore vary across firms. In that case, firms with a lower default risk might show higher CoPSD values simply because they have been conditioned on a more extreme event; see also Adrian and Brunnermeier (2016).

potential losses to the overall economy in terms of aggregate output.[8]

Defining the CoPD and the CoPSD under the risk-neutral measure warrants an additional remark on their interpretation. Since they are risk-neutral, both risk measures incorporate not only physical probabilities, but also a risk premium component reflecting the risk preferences of the market participants. The CoPD and the CoPSD therefore reflect the full set of market information on distress risk, and are best interpreted as risk-adjusted likelihood indicators of the underlying events.[9]

3.3. Estimating Credit Risk Parameters

We base our analysis of systemic risk on probabilities of default and asset return correlations estimated from CDS spreads. CDS are credit derivatives that offer protection against the risk that a specify entity defaults on its debt. The underlying entity is known as the *reference entity* and default by the entity is referred to as *credit event*. The protection buyer pays the protection seller a periodic spread on the contract notional until either the contract matures or a credit event occurs, whichever is first. In return, the protection seller promises to cover default losses should a credit event occur during the life of the contract. Default losses are measured as the difference between the nominal value and the post-default value of a particular bond issued by the reference entity.[10]

CDS spreads offer several advantages over other credit risk indicators such as bond or loan spreads and ratings. CDS spreads have been reported to be a relatively pure measure of credit risk compared to bond spreads (Longstaff et al., 2005) while being only very marginally affected by counterparty risk due to collateralization (Arora et al., 2012).[11] Moreover, the CDS market has been found to lead the bond market (Blanco et al., 2005; Forte and Peña, 2009) and the loan market (Norden and Wagner, 2008) in price discovery and to anticipate rating announcements (Hull et al., 2004). In the context of our study, Rodríguez-Moreno and Peña (2013) report the CDS market to be a better indicator of systemic distress compared to the stock market. We expect these informational advantages

[8]We refer to Borio (2003) for a discussion of microprudential and macroprudential regulation.

[9]See also the related discussion in Malz (2013, p. 2). The DIP framework set out in the previous section offers an alternative interpretation of the CoPD and the CoPSD as conditional unit prices of systemic risk. Indeed, consider the marginal DIP of firm i in Equation (3.10) conditional on a systemic event:

$$DIP_{i,t\,|\,L_{\mathcal{S},t+h}>SLT}\,(h) = \left(1 - \overline{RR}_{i,t+h}\right) \cdot X_i \cdot CoPD_{i,t}\,(h) \cdot e^{-rh},$$

where $\overline{RR}_{i,t+h}$ is the expected recovery rate. Conditional on a systemic event, the marginal DIP is linear in the expected loss at default and the CoPD. In other words, CoPD is the compounded insurance premium for one unit of firm i's marginal ETL if a systemic event occurs. Likewise, CoPSD is the compounded insurance premium for one unit of the financial system's ETL if firm i is in distress.

[10]CDS mimic the payout profile of an insurance contract. However, while CDS have been referred to as insurance, they are not as they lack the notion of *insurable interest*: the protection buyer is not required to hold debt issued by the reference entity, and market participants can therefore use CDS to speculate on a default by the reference entity. CDS are also not treated as insurance for regulatory purposes.

[11]Non-default components in bond prices are primarily driven by illiquidity (Longstaff et al., 2005). Other factors such as short-sale restrictions, taxes, and embedded options may add further to a distortion of bond prices (Blanco et al., 2005; Longstaff et al., 2005).

to be reflected in our CDS-implied systemic risk measures.

Several recent studies on systemic risk have relied on probabilities of default estimated from CDS spreads, including, e.g., Huang et al. (2009, 2012a,b), Chen et al. (2014), and Black et al. (2016). In these studies, asset return correlations have been estimated from equity returns. We additionally infer the asset return correlations from CDS spreads rather than from equity returns for two main reasons. First, estimating both parameters from the same instrument ensures their internal consistency. Within the Merton (1974) model, equity and debt can be interpreted as call and put options on a firm's assets, respectively. Equity and debt markets should thus tend to co-move with the asset value.[12] However, while theoretically conveying equivalent information on asset values, equity and debt markets may behave differently in practice. The instruments traded in these markets refer to distinct parts of the firms' capital structure. Parts of the capital structure may enjoy explicit or implicit guarantees, and the market prices of the guaranteed instruments will reflect a level of credit risk net of the guarantee (Dwyer et al., 2010).

Moreover, estimating default probabilities and correlations from CDS spreads makes our modeling framework applicable to non-traded entities such as private firms or subsidiaries of public firms. Modeling private firms is of particular practical relevance for the European banking sector with its relatively high share of non-listed savings and co-operative institutions.[13] Modeling subsidiaries of public firms allows analyzing financial groups consolidating non-listed insurance and banking entities at the subsidiary level, hence enabling a more precise allocation of systemic risk between sectors.

3.3.1. Probabilities of Default

We estimate *risk-neutral* default probabilities from CDS spreads using the reduced-form valuation framework described in Duffie (1999) and Hull and White (2000). Under no-arbitrage, the expected present value of the spread payments of the protection buyer in the premium leg (the left-hand side of the following equation) initially equals the expected present value of the default loss payment of the protection seller in the protection leg (the right-hand side of the equation) so that the initial value of the CDS contract is zero:

$$\int_t^{t+T} s_{i,t} e^{-r_\tau(\tau-t)} Q_{i,\tau} d\tau = \int_t^{t+T} (1 - RR_{i,t}^{CDS}) e^{-r_\tau(\tau-t)} q_{i,\tau} d\tau. \tag{3.15}$$

$RR_{i,t}^{CDS} \in [0,1]$ is the time t expectation of the recovery rate on the underlying debt, $s_{i,t}$ is the annual spread, $q_{i,\tau}$ is the risk-neutral default intensity, $Q_{i,\tau} = 1 - \int_t^\tau q_{i,\nu} d\nu$ is the associated risk-neutral survival probability up to time τ, and T is the tenor of the contract.[14] Under the usual simplifying assumption that the term structures of the risk-

[12] Assuming constant leverage, the relationship is exact; see Huang et al. (2009, Appendix A) for a proof.

[13] Taking Germany as an example, seven of the ten banks in our sample are not publicly listed. Six of these banks are *Landesbanken*, the head institutions of the regional savings banks; see Appendix B.

[14] We assume that the recovery rate is independent of the risk-free rate and the default intensity.

free rate and the default intensity are flat, $r_\tau = r_t$ and $q_{i,\tau} = q_{i,t}$ for all $\tau \in [t, t+T]$, we solve for the one-year risk-neutral probability of default:

$$q_{i,t} = \frac{as_{i,t}}{a(1 - RR_{i,t}^{CDS}) + bs_{i,t}}, \tag{3.16}$$

where we let $a = \int_t^{t+T} e^{-r_t(\tau - t)} d\tau$ and $b = \int_t^{t+T} (\tau - t) e^{-r_t(\tau - t)} d\tau$.

3.3.2. Asset Return Correlations

Following Duellmann et al. (2010), market-based estimation approaches for asset return correlations fall into *indirect* approaches that infer the correlations from prior estimates of the unobserved market value of assets, and *direct* approaches that calculate the correlations directly from observed market prices. In the literature, Lopez (2004) follows the indirect approach using asset values estimated from equity and financial statements data. Byström (2011) follows the indirect approach using an asset value proxy based on equity and CDS data. Huang et al. (2009) implement the direct approach based on equity returns. Tarashev and Zhu (2008) apply the direct approach using CDS spreads.[15]

We implement the method of Tarashev and Zhu (2008). To be precise, we estimate *physical* asset return correlations from the CDS-implied risk-neutral probabilities of default recovered in the previous section (Tarashev and Zhu, 2008, p. 8):

$$\begin{aligned} \rho_{ij} &= \operatorname{corr}\left(R_{i,t:t+h}, R_{j,t:t+h}\right) \\ &= \operatorname{corr}\left(\Delta\Phi^{-1}\left(PD_{i,t}\left(h; D_i\right)\right), \Delta\Phi^{-1}\left(PD_{j,t}\left(h; D_j\right)\right)\right) \\ &\approx \operatorname{corr}\left(\Delta\Phi^{-1}\left(q_{i,t}\right), \Delta\Phi^{-1}\left(q_{j,t}\right)\right). \end{aligned} \tag{3.17}$$

In the second line, we make the transition to discrete time. Δ denotes the usual difference operator. The third line serves as an approximation since Equation (3.4) violates the assumption of a flat term structure of default intensities which was used when deriving the one-year risk neutral probability of default, $q_{i,t}$, in Equation (3.16).[16]

Based on Equation (3.17), we first estimate non-parametric pairwise correlations $\hat{\rho}_{ij}$. Due to missing data for some firms, the outcome of the pairwise estimation process is not guaranteed to yield a consistent correlation structure. Specifically, the matrix $\hat{C}$ defined by $\left[\hat{C}\right]_{ij} = \hat{\rho}_{ij}$ may fail to be positive semi-definite and will then not be valid as a correlation

[15] As an alternative to the market-based approach, the correlation structure underpinning our modeling framework could theoretically also be estimated from historical default events. The correlation of corporate defaults has been analyzed in several empirical studies (e.g., Dietsch and Petey, 2004; Das et al., 2007). We do not pursue this approach as data on simultaneous defaults are scarce, even more so for investment-grade insurers and banks, which could give rise to a potentially severe estimation bias in our setting. Duellmann et al. (2010) confirm the superiority of market-based estimation approaches in a simulation study comparing asset return correlations estimated from default intensities and stock prices.

[16] The approximation could be avoided using Equation (3.4) directly in Equation (3.15). Robustness tests conducted by Tarashev and Zhu (2008) confirm that the correlation estimates are insensitive to the resulting misspecification. We thus stick to Equation (3.17) for the sake of parameter parsimony.

matrix. This is automatically resolved when fitting the factor model of Equation (3.1) to the raw estimates. Minimizing the sum of squared element-wise deviations, we obtain the following optimization problem for the M-factor correlation structure:

$$\begin{aligned} \min_{F_1,\ldots,F_N} \quad & \sum_{i=2}^{N}\sum_{j=1}^{i-1}\left(\hat{\rho}_{ij} - F_i F_j^\top\right)^2 \\ \text{s.t.} \quad & F_i F_i^\top \leq 1, \qquad\qquad i = 1,\ldots,N, \end{aligned} \tag{3.18}$$

where we recall that $F_i = [F_{i,1},\ldots,F_{i,M}]$ is a row vector of M factor loadings. We solve the optimization problem using the principal factors method of Andersen et al. (2003).[17]

4. Empirical Data

The data set used in our empirical analyses is a panel of global banks and insurers for the period from January 2004 through December 2014. The data set includes CDS data taken from Thomson Reuters Datastream and financial statements data taken from Bloomberg. We retrieve daily mid-spreads for 5-year senior unsecured CDS contracts and annual total liabilities. We aggregate the daily spreads to weekly spreads and use linear interpolation within fiscal years to compute weekly portfolio weights from the annual total liabilities. Appendix A provides a detailed description of our data sources and definitions.

In the following, we outline the selection of the sample financial firms and describe the data set for the resulting sample financial system. We further estimate the credit risk parameters of our portfolio credit risk model and describe their dynamics.

4.1. Sample Selection

We select our sample from the full list of reference entities with a matching single-name CDS contract on Thomson Reuters Datastream. We first build an initial banking sample of commercial and investment banks and an initial insurance sample of insurance and reinsurance carriers starting from Industry Classification Benchmark (ICB) subsectors. We then restrict the final sample to firms that have a sample period worth at least two years of weekly firm observations. Each firm in the final sample is assigned to one of six sector subsamples depending on its main business activity: *banking*, *multi-line insurance*, *life insurance*, *P/C insurance*, *financial insurance*, and *reinsurance*.[18]

[17] Note that Equation (3.18) defines a non-convex optimization problem for $M > 1$. In the multifactor case, we can thus generally only expect to find a local minimum. Borsdorf et al. (2010) provide a detailed discussion of the optimization problem and suitable solution approaches.

[18] The ICB subsector codes represented in the final sample are 8355, 8532, 8536, 8538, 8575, 8777, and 8779. We map the subsector codes into our subsamples as follows: the banking sample includes all commercial banks from the subsector 8355 and all investment banks from the subsector 8779; the multi-line insurance sample includes all firms from the subsector 8532; the life insurance sample includes all firms from the subsector 8575; the P/C insurance sample includes all firms except financial guarantee insurers from the subsector 8536; the financial insurance sample includes all financial guarantee insurers from the subsector 8536 and all private mortgage insurers from the subsector 8779; and the reinsurance sample

At the firm level, we adjust the sample periods for in-sample consolidation and failures. CDS contracts may trade for all debt-issuing firms within a corporate group. Indeed, several firms in the initial sample are subsidiaries of other sample firms for all or part of the sample period. Corporate group structures change as sample firms engage in mergers and acquisitions, and we observe a trend towards increasing consolidation during the sample period. As we model losses based on total liabilities, including a parent firm and one of its subsidiary firms in the sample would give rise to concern due to a potential double-counting of losses. The consolidated financial statements of the parent firm include the liabilities of the subsidiary firm, and the impact of the corporate group on aggregate losses would be overstated if both the parent firm and the subsidiary firm were to default. We therefore exclude firms from the sample for any period in which they are direct or indirect subsidiaries of other sample firms. Following this approach, we generally keep only the ultimate parent firm of a corporate group in the sample for any given date. We recursively build the dynamic corporate group structure data used in this exercise from static group structure data and mergers and acquisitions data.[19]

ING Groep of the Netherlands and KBC Groep of Belgium provide for an exception to this general rule. During our sample period, each of these financial holding companies operates through two principal subsidiaries: a banking subsidiary and an insurance subsidiary. In the case of ING Groep, the holding company, the banking subsidiary, and the insurance subsidiary are all part of our initial sample; in the case of KBC Groep, our initial sample comprises the holding company and the banking subsidiary. We exclude the holding companies in favor of the subsidiary companies in order to achieve a more precise allocation of systemic risk to the insurance and banking sectors.

Several firms represented in the initial sample fail during our sample period. On each date, we restrict our sample to non-defaulted firms that are actively accepting new business. We therefore exclude firms from the sample once they either experience a credit event, i.e., fail to pay on one of their obligations, enter bankruptcy proceedings, or restructure their debt, or once they enter an orderly resolution process.[20]

4.2. Data Set

Table 1 shows descriptive statistics on the composition, liability size distribution, and CDS spreads of the sample financial firms. In our sample, there are 183 financial firms, including 133 banks and 50 insurers. There are 38 financial firms from Northern America, 92 from Europe, and 53 from other regions. In total, the sample financial firms represent

includes all firms from the subsector 8538. Our sample therefore excludes central banks classified in the subsector 8355, deposit insurance schemes classified in the subsector 8536, non-bank financial firms such as market infrastructures and online brokers classified in the subsector 8777, and non-insurer financial firms such as government-sponsored enterprises and building societies classified in the subsector 8779.

[19] The static group structure and mergers and acquisitions data are taken from Bloomberg.

[20] Data on credit events are taken from the International Swaps and Derivatives Association. Data on orderly resolution processes are obtained checking the sample firms' investor relations websites.

34 countries. The banking sample covers 28 of the 34 banks that have been designated as global systemically important banks (G-SIBs) based on data from our sample period, and the insurance sample covers nine of the ten insurers that have received G-SII status based on data from our sample period.[21] Appendix B lists the sample financial firms.

Based on financial statements data for 2009, the largest sample banks by total liabilities are BNP Paribas (USD 2,834 billion), Royal Bank of Scotland Group (USD 2,587 billion), and HSBC Holdings (USD 2,229 billion). The largest sample insurers are AXA (USD 943 billion), Allianz (USD 776 billion), and AIG (USD 749 billion). The liability size distribution is heavily skewed to the right, with a median of USD 211 billion for banks and USD 86 billion for insurers. The aggregate liabilities of the sample financial system amount to USD 68,353 billion, with USD 59,035 billion owed by the banking sector and USD 9,318 billion owed by the insurance sector. To put the liability sizes into perspective, the largest sample banks are each about the same size as the United Kingdom's gross domestic product at that time, and the sample banking sector as a whole is about the same size as the world's gross domestic product at that time. This corroborates the common too-big-to-fail concern, as the default of a limited number of financial institutions could trigger losses equivalent to the gross domestic product of entire countries.

For the year 2009, the sample banks account for 47 percent of the worldwide banking industry assets, and the sample insurers account for 44 percent of the worldwide insurance industry assets as reported by the FSB (2015a).[22] This has two important implications for our analyses. First, the banking sample and the insurance sample are representative of the industries' level of systemic risk. Either sample covers a significant part of the industries' assets, including most of the industries' largest firms, among them most of the industries' G-SIFIs. The samples should therefore reflect most of the systemic risk in the respective industry. Second, the banking sample and the insurance sample scale the worldwide banking and insurance industry assets at approximately the same proportion. We can therefore make valid inferences on the relative contribution of the banking and insurance sector to the level of systemic risk in the financial system.

Turning to the CDS spreads, we report mean spreads for 5-year senior unsecured CDS contracts of the sample firms. We consider four periods: the full sample period

[21] We count a financial institution as G-SIFI if it either (i) has been included on one of the lists of G-SIBs published by the FSB from 2011 through 2015, (ii) has been included on one of the lists of G-SIIs published by the FSB from 2013 through 2015, or (iii) operates as a principal subsidiary of one of these firms. Each annual update of the G-SIFI lists is based on data as per the end of the previous year. The timeframe considered by the FSB to assess the status of these G-SIFIs is therefore consistent with our sample period. The insurance sample excludes G-SII Ping An, since we could not identify a CDS contract for this firm.

[22] FSB (2015a) reports the assets of different types of financial institutions for the Eurozone and 20 additional jurisdictions, including the United States, the United Kingdom, and Japan. The asset definition extends to financial assets where available and to total assets otherwise. In total, the data cover 90 percent of global financial system assets (FSB, 2015b, p. 1). We relate the assets of the banking sample to the assets reported for deposit-taking institutions and broker-dealers, and the assets of the insurance sample to the assets reported for insurance companies.

from January 2004 through December 2014; the pre-crisis period, taken as January 2004 through July 2007; the period of the financial crisis and the intermittent recovery, taken as August 2007 through April 2010; and the period of the European sovereign debt crisis and the subsequent recovery, taken as May 2010 through December 2014.

The spreads show considerable time series and cross-sectional variation. The mean spread of the full sample was at 33 basis points in the years leading up to the financial crisis. The period of the financial crisis saw a more than eight-fold increase of the mean spread level, then averaging 277 basis points. During the period of the European sovereign debt crisis, the mean spread receded mildly, then averaging 232 basis points, seven times the pre-crisis value. Banks and insurers show different dynamics during the sample period. In the pre-crisis period, the sample banks had a mean spread of 28 basis points, less than the sample insurers, which had a mean spread of 42 basis points. The mean spread of the sample banks then increased to 193 basis points for the period of the financial crisis and, driven by European banks, increased further to 227 basis points for the period of the European sovereign debt crisis. The mean spread of the sample insurers increased to 471 basis points for the period of the financial crisis, and receded to 247 basis points for the period of the European sovereign debt crisis. P/C insurers and reinsurers had the lowest overall spread levels, and financial insurers had the highest overall spread levels.

4.3. Model Estimation

The full set of parameter estimates for each sample firm includes probabilities of default, asset return correlations, and recovery rates. We estimate weekly time series of risk-neutral probabilities of default and asset return correlations from the CDS spreads described in the previous section. We calculate the risk-neutral probabilities of default for a one-year horizon and use a rolling window of one year to estimate the asset return correlations. Using a rolling window of one year for the estimation of the asset return correlations effectively limits the horizon for our systemic risk analyses to the period from January 2005 through December 2014. Following market convention, we assume a recovery rate of 40 percent for the senior unsecured debt underlying the CDS contracts.[23]

Figure 1 plots the time series of the risk-neutral probabilities of default. We report the mean, median, lower 5 percent quantile, and upper 5 percent quantile for the financial system, and additionally the mean and median of each sector. The risk-neutral probabilities of default reflect the time series and cross-sectional variation of the CDS spreads. Risk-neutral probabilities of default were low prior to the financial crisis. Across sectors, they increased at the onset of the financial crisis and peaked at various events during the financial crisis and the European sovereign debt crisis. The banking sample faced similar levels of default risk during the financial crisis and the European sovereign debt crisis,

[23]The results of Jankowitsch et al. (2014) lend support to this practice. In a study on recovery rates in the U.S. corporate bond market, they report a mean recovery rate of 39 percent on defaulted senior unsecured bonds over the period from July 2002 to October 2010.

whereas the mean risk-neutral probabilities of default of the insurance samples peaked at higher values during the financial crisis compared to the European sovereign debt crisis. Over the full sample period, P/C insurers and reinsurers tended to have the lowest default risk, and financial insurers had the highest default risk.

Figure 2 plots the time series of the asset return correlations. For each firm, we compute the average asset return correlation between the firm and all other firms in the sample financial system. We show the mean, median, lower 5 percent quantile, and upper 5 percent quantile of the firm correlations for the financial system, and additionally the mean and median of the firm correlations for each sector. We observe a regime shift at the onset of the financial crisis. During the pre-crisis period, the mean asset return correlation of the full sample was 25 percent; during the financial crisis and European sovereign debt crisis, mean asset return correlations were almost twice as high, averaging 48 percent. Across sectors, asset return correlations were highest during the period from August 2007, when the subprime mortgage crisis eventually spilled over to other financial markets, to September 2008, when Lehman Brothers filed for bankruptcy.

The recovery rate estimates required for default scenarios represent the share of total liabilities that creditors will ultimately recover after default. These recovery rates thus refer to the entire liability structure, as opposed to the recovery rate used in the estimation of the risk-neutral probabilities of default, which refers to senior unsecured debt. The recovery rate of the sample banks and insurers will mainly be driven by the individual firm's post-default asset quality. Insurers generally hold a higher share of liquid assets compared to banks, and we therefore expect insurers to have higher recovery rates on average.

Figure 3 shows the average liability composition of the sample banking and insurance sectors. Broadly, banks' liability structure comprises customer deposits, borrowings, and other liabilities; and insurers' liability structure comprises technical provisions, borrowings, and other liabilities. Technical provisions form the largest part of insurers' liabilities. They serve to cover unexpired risk from insurance policies and to meet unsettled policyholder claims. Insurance regulators are particularly concerned with the quality of the assets invested in support of the technical provisions, which are generally more tightly regulated.[24] To the extent that this regulation is effective, it should result in a particularly high recovery rate for the portion of insurers' assets invested in support of the technical provisions.

The post-default value of individual financial institutions' assets is hard to estimate.[25]

[24]The first set of Insurance Core Principles explicitly required that "Standards should be established with respect to the assets of companies [...] these should apply at least to an amount of assets equal to the total of the technical provisions" (IAIS, 2000, p. 9). In their report on Insurance and Financial Stability insurance regulators proclaimed that "ensuring the quality and safety of invested assets in support of these provisions comprise the core functions of the traditional insurance business. Under the model, insurers often pursue also an appropriate duration matching of assets to liabilities" (IAIS, 2011, p. 8).

[25]Previous studies have therefore relied on ad hoc chosen values for the recovery rate (Huang et al.,

In the absence of reliable estimates of the recovery rates of individual banks and insurers, we use mean recovery rates for all banking firms and for all insurance firms, which we approximate as follows. For insurers, we assume a recovery rate of 80 percent for the assets invested in support of the technical provisions. Talks with experts involved in regulatory affairs have led us to the conclusion that this represents severe yet plausible distress for these investments. We further assume a recovery rate of 40 percent for the assets invested in support of borrowings and other liabilities. This choice is guided by the market practice for senior unsecured debt. For banks, we follow a parallel procedure and assume a recovery rate of 80 percent for the assets invested in support of customer deposits, and a recovery rate of 40 percent for assets invested in support of borrowings and other liabilities. For the time series of mean recovery rates of the banking and insurance sector we weight the liability-specific recovery rates with the respective liability shares of these sectors.[26]

Figure 3 plots the resulting time series of recovery rates. We observe low variation overt time for either sector. The recovery rates used in our study average 57 percent for the banking sample, and 72 percent for the insurance sample.

The recovery rates for banks compare well to the results of James (1991), who reports average costs of failure to assets of 40 percent for U.S. bank failures in the mid-1980s. Bennett and Unal (2015) document lower costs of failure of 33 percent for U.S. bank failures in the period from the mid-1980s through 2007. However, we expect the costs of bank failures during the financial crisis and the European sovereign debt crisis to be higher than this long-year average due to generally deteriorated asset values.

We are not aware of a comparable study on the costs of failure for life or reinsurance companies. Hall (2000) and Grace et al. (2005) document very high costs of failures for U.S. P/C insurer failures in the 1980s and 1990s, on average even exceeding the assets of the failed institution. However, the results obtained in these studies relate to very small P/C insurers with assets of often only several million U.S. dollars, and are therefore not applicable to the insurers considered in our analysis.

5. Findings on Systemic Risk

We analyze systemic risk in insurance applying the methodology of the previous sections. We organize our analysis in four steps. First, we analyze the time series of systemic risk in the global financial system and determine the contribution of the different subsamples to aggregate systemic risk. Second, we study the time series of banking sector

2009; Puzanova and Düllmann, 2013; Chen et al., 2014), or have used time series of CDS-implied recovery rates referring to senior unsecured debt (Huang et al., 2012a,b; Black et al., 2016).

[26] Note that this does not make or imply any assumptions on the recovery rates realized by the different types of creditors. The average recovery rates realized by depositors, policyholders, investors, and other creditors will depend on the seniority of their claims as determined by the bankruptcy law of the financial institution's jurisdiction.

and insurance sector distress risk. Third, we consider the cross section of financial institutions in the global sample financial system and determine the level of systemic risk associated with each individual institution. As a final analysis, we study the input factor determinants of our systemic risk measures.

For the purpose of empirical illustration, we define systemic events as a loss in aggregate sector liabilities of more than 10 percent over a one-year horizon. We further define that a financial institution is in severe distress if it falls short of the lower 1 percent quantile of its asset return distribution over the same horizon. All risk measures are evaluated in weekly frequency to closely track the events during the financial crisis and the European sovereign debt crisis. To ease our exposition, we sometimes will report average values for the crisis periods. We define the financial crisis and intermittent recovery as the period from August 2007 through April 2010, and the European sovereign debt crisis and subsequent recovery as the period from May 2010 through December 2014, the end of our sample period.

5.1. Financial System Systemic Risk

In this section, we consider the entire sample global financial system. We first study the time series of aggregate systemic risk and the underlying risk components. We then analyze the marginal risk contributions by sector and region.

5.1.1. Time Series of Systemic Risk

Figure 4 plots the time series of systemic risk in the sample global financial system. Systemic risk is measured using the aggregate DIP indicator, defined as the premium of a hypothetical insurance contract protecting debt holders against systemic losses. This premium is reported in nominal price expressed in U.S. dollars in Figure 4a, and in unit price relative to aggregate total liabilities in Figure 4b. The nominal price of systemic risk scales with the aggregate liabilities in the sample. To compare systemic risk on a common scale over time, we focus on unit prices and report nominal prices in parentheses.

The level of systemic risk shows considerable time series variation, and reflects major events during the financial crisis and the ensuing European sovereign debt crisis. At the beginning of our sample period, the level of systemic risk is low, averaging less than 1 basis point (USD 3 billion) during the two and a half years from January 2005 up to the end of July 2007. As the financial crisis begins to spill over from the U.S. subprime mortgage market to the broader financial system, the level of systemic risk increases remarkably. By August 10, 2007, one day after BNP Paribas froze three funds with exposure to the U.S. subprime mortgage market, the level of systemic risk has jumped to 12 basis points (USD 64 billion). There are three distinct peaks in the systemic risk indicator during the financial crisis. The first peak marks the week of March 14, 2008, immediately before the takeover of Bear Stearns by JPMorgan Chase. The second peak marks the period between the middle of September 2008 and the beginning of October 2008, when Lehman Brothers filed for bankruptcy, AIG received government support, and Washington Mutual was seized. The third and final peak marks the week of March 13, 2009, when systemic risk stands at its highest value during the financial crisis, 83 basis points (548 billion), just when U.S. stock markets reached their lowest point during the financial crisis. Following the last peak, the systemic risk indicator starts to trend downward. In the third quarter of 2009, during the intermittent recovery period, the level of systemic risk in the sample global financial system is valued at around 21 basis points (USD 139 billion).

Early warning signals of the looming European sovereign debt crisis became visible during the intermittent recovery period, as the Greek government revised its budget deficit, and as major rating agencies downgraded long-term Greek sovereign debt. The level of systemic risk increases again as the European sovereign debt crisis aggravates and reaches a temporary high of 56 basis points (USD 378 billion) for the week of June 11, 2010, six weeks after the first support package for Greece was agreed between the European Commission, the European Central Bank, the International Monetary Fund, and the Greek government. The period between autumn 2011 and summer 2012 appears to mark the height of the European sovereign debt crisis. For the week of November 25, 2011, the level of systemic risk reaches its highest value during our sample period at 92 basis points (USD 625 billion). In the following months, the systemic risk indicator trends downward again. In the second half of 2014, during recovery from the core European sovereign debt crisis and towards the end of our sample period, systemic risk averages 11 basis points (USD 75 billion), about the same level as at the beginning of the financial crisis.

The financial crisis and the European sovereign debt crisis triggered a range of policy responses by central banks and governments. Central banks reduced interest rates and provided liquidity support. Governments recapitalized or guaranteed troubled financial institutions. As part of their crisis interventions, the Federal Reserve Bank, the European Central Bank, and the Swiss National Bank announced a joint enhancement of liquidity-providing measures at the beginning of May 2008. Five months later, early in October 2008, the U.S. Congress approved the USD 700 billion Troubled Asset Relief Program, the U.K. government announced a USD 850 billion bank rescue package, and the French government released a USD 480 billion bank rescue plan.

Two interesting observations can be made with respect to these exemplary policy responses. First, the level of systemic risk was lower around the time of either intervention, only to hike up again after several months. Therefore, while these policy measures may have succeeded in calming markets short-term, they did not succeed in reducing systemic risk over an extended period. Moreover, the total amount of government support for the financial system seemingly exceeds the level of systemic risk reported above significantly. This apparent difference stems from the fact that we measure systemic risk as the present value of *expected* losses over a one-year horizon, whereas the government support relates to *realized* funding needs or losses.

The level of systemic risk as measured by the DIP indicator factors into two components: the likelihood of a systemic event, measured by the risk-neutral PSD, and the expected severity of a systemic event, measured by the ETL. We will disentangle these drivers of aggregate systemic risk in the following.

Figure 5 plots the time series of these systemic risk components. Figure 5a shows the risk-neutral PSD and Figure 5b shows the ETL in unit price relative to aggregate liabilities. The PSD accounts for most of the time series variation in the relative DIP indicator. On its own, it explains 99 percent of the observed variation. The risk-neutral PSD is virtually zero in the years leading up to the financial crisis, and closely tracks major crisis events. The highest value during the financial crisis is reached at 4.6 percent for the week of March 13, 2009, when U.S. stock markets reached their financial crisis low. The highest value during our sample period is assumed at 5.5 percent for the week of November 25, 2011, during the height of the European sovereign debt crisis.

The ETL shows considerably less time series variation. On its own, it explains 58 percent of the observed variation in aggregate DIP. We observe a level shift in the ETL with the onset of the financial crisis. During the pre-crisis period, the ETL averages 13 percent, and during the period of the financial crisis and the European sovereign debt crisis, the ETL averages 17 percent. The ETL peaks at about 20 percent during the period from mid-March 2009, when Bear Stearns was taken over, through late September 2009, the immediate aftermath of the Lehman Brothers bankruptcy.

The dynamics of the PSD and the ETL shed light on the market assessment of systemic risk. Within our framework, the severity of systemic events increases only moderately during the crisis episodes. The considerable increase in systemic risk discussed above is mainly driven by an increase in the risk-adjusted likelihood of a systemic event, which reflects the cost to protect against a unit of expected default loss. This increase may be attributed to a combination of increased physical default probabilities, and increased risk aversion in times of crisis (see, e.g., Huang et al., 2012b; Black et al., 2016).

5.1.2. Sector and Region Contributions

For a given level of systemic risk, the interesting question then is to identify the vulnerabilities of the financial system, i.e., the sectors and regions with the highest marginal contribution to systemic risk. Figure 6 plots the systemic risk contributions of the different sectors in the sample global financial system over time. Figure 6a shows the marginal contributions in unit price and Figure 6b shows the marginal contributions as share of total risk. The marginal contributions of the banking and insurance sector follow a similar trajectory, albeit at different levels. Throughout the sample period, the banking sector contributes most systemic risk. During the financial crisis and the European sovereign debt crisis, the banking sector on average accounts for 91 percent of aggregate systemic losses, and the insurance sector accounts for 9 percent. The systemic risk contribution of the insurance sector is mostly driven by multi-line insurance and life insurance. Each of these insurance sectors on average accounts for about 4 percent of aggregate systemic losses during the crisis episodes, while the remaining insurance sectors collectively account for about than 1 percent. The marginal contributions of the banking and insurance sector are relatively constant over time, with a somewhat higher systemic risk contribution of the insurance sector at the beginning of the financial crisis of about 14 percent. This provides evidence that the insurance sector in aggregate is not a major contributor to systemic risk. The contributions of different sectors to aggregate systemic losses reflect their liability sizes. Therefore, the sectors' marginal risk contributions are not indicative of their relative riskiness. Moreover, while the aggregate contribution of the insurance sector is limited, individual insurance firms may still be systemically important. We will analyze the distress risk of the banking and insurance sector in Section 5.2, and will discuss the systemic importance of individual financial institutions in Section 5.3.

We further assess the marginal contribution to systemic risk by macroeconomic region. Figure 7 plots the systemic risk contributions of the different regions in the sample global financial system over time. Figure 7a reports the marginal contributions in unit price and Figure 7b reports the marginal contributions as a share of total risk. Europe contributes the highest share of systemic risk throughout the sample period. During the financial crisis and European sovereign debt crisis, Europe on average accounts for 71 percent of systemic losses, Northern America on average accounts for 17 percent, and the other regions combined on average account for 12 percent. We observe a continued increase in Europe's relative systemic risk contribution between May 2010, when the first support package for Greece was agreed, and August 2011, when global stock markets fell. This may be seen as evidence that a concentration of systemic risk built up in Europe during the early stages of the European sovereign debt crisis which subsequently spilled over to other economies.

5.2. Banking and Insurance Sector Distress Risk

In this section, we analyze the risk of banking and insurance crises. We apply our modeling framework separately to each sample sector. Following this approach, distress risk at the sector level is measured by the aggregate DIP indicator. This risk metric is now defined as the premium of a hypothetical insurance contract protecting the sector's debt holders against distressed sector losses, irrespective of the state of the broader financial system. We first consider the global banking and insurance sectors; then we turn to the different lines of insurance.

5.2.1. Global Banking and Insurance Sectors

Figure 8 plots the time series of banking and insurance sector distress risk. Figure 8a refers to the banking sector and Figure 8b refers to the insurance sector. The left-hand panels show the level of distress risk in nominal price expressed in U.S. dollars, and the right-hand panels show the level of distress risk in unit price relative to aggregate total sector liabilities. The nominal price of distress risk reflects the different liability sizes of the sectors, whereas the unit price refers to the distress risk per unit of exposure. The unit price therefore compares the banking and insurance sector on a common scale.

The distress risk of either sector was very low in the years leading up to the financial crisis, averaging less than 1 basis point (USD 3 billion) for the banking sector and about 2 basis points (USD 1 billion) for the insurance sector. During the ensuing financial crisis and European sovereign debt crisis, both sectors experience increased levels of distress, averaging 44 basis points (USD 251 billion) for the banking sector and 25 basis points (USD 24 billion) for the insurance sector. The distress risk of the banking sector peaks at 102 basis points (USD 601 billion) for the week of November 25, 2011, during the height of the European sovereign debt crisis. The distress risk of the insurance sector peaks at 96 basis points (USD 87 billion) for the week of March 13, 2009, during the time of the financial crisis U.S. stock market low.

The combined nominal distress risk of the banking sector and the insurance sector consistently exceeds the nominal systemic risk of the full financial system reported in Figure 4a, confirming that our modeling framework adequately captures the benefits of diversification. During the financial crisis and the European sovereign debt crisis, the nominal distress risk of the insurance sector on average amounts to only 10 percent of the nominal distress risk of the banking sector. This share ranges between a low of 6 percent in early August 2011, and a high of 26 percent in mid-October 2008. The low absolute distress risk of the insurance sector relative to the banking sector lends further support to the hypothesis that the aggregate systemic risk of the insurance sector is rather confined. This is consistent with the low marginal contribution of the insurance sector to systemic risk in the global financial system reported in Figure 6b.

There is an interesting time pattern in the ordering of the relative distress risk of the two sectors over the sample period. From the beginning of the sample period up to the onset of the financial crisis, the unit price of distress risk in the banking and insurance sectors is very similar, though the insurance sector is slightly more risky on average. From the onset of the financial crisis up to September 2008, the banking and insurance sector closely track each other, with the peaks of the insurance sector falling below those of the banking sector. Qualitatively similar results for the pre-crisis period and the early stage of the financial crisis have also been reported by Chen et al. (2014).

Following the bankruptcy of Lehman Brothers and the near-bankruptcy of AIG in mid-September 2008, the spread of the banking sector over the insurance sector closes. For several weeks in the period from October 2008 through May 2009, the insurance sector even has a higher relative distress risk than for the banking sector.

During the following intermittent recovery period, which saw the U.S. leaving recession, and throughout the European sovereign debt crisis, the relative distress risk of the banking sector dominates that of the insurance sector. The spread of the banking sector over the insurance sector first widens, and reaches its highest value in the fourth quarter of 2011, at the height of the European sovereign debt crisis. During the subsequent recovery period and towards the end of our sample period, the spread narrows again.

To investigate this observation further, we analyze the components of distress risk plotted in Figure 9. The time series for the banking sector are shown in Figure 9a, and the time series for the insurance sector are shown in Figure 9b. The left-hand panels show the risk-neutral PSD, and the right-hand panels show the ETL in unit price. The PSD accounts for most of the time series variation in the sectors' distress risk. The risk-adjusted likelihood of distress in either sector is very low during the pre-crisis period, though it is marginally higher for the insurance sector. There are three distinct phases in the relationship of the sectors' PSD during the crisis periods. First, during the early phase of the financial crisis up to early October 2008, the PSD is higher for the banking sector. Then, for the period from mid-October 2008 up to early June 2009, the insurance sector tends to have a higher PSD. Finally, from mid-June 2009 up to the end of our sample period, the relationship reverses again and the banking sector has a higher PSD.

The ETL shows different dynamics. The ETL is very similar for both sectors during the pre-crisis period. With the onset of the financial crisis, the ETL increases for both sectors; however, throughout the financial crisis and the European sovereign debt crisis, the ETL of the banking sector dominates that of the insurance sector. In other words, during that period, banking crises were expected to impair a larger share of the banking sector compared to the effect of insurance crises on the insurance sector.

In summary, the nominal distress risk of the insurance sector consistently only accounts for a fraction of the nominal distress risk of the banking sector. The relative riskiness of the two sectors, however, appears to depend on the market situation. In times of severe distress, the insurance sector may turn out to be more risky per unit of exposure than the banking sector. For the episode of the fourth quarter of 2008 and the first quarter of 2009, this can be attributed to a higher risk-adjusted likelihood of insurance sector crises, rather than to a higher expected severity of insurance sector crises compared to banking sector crises. In the fourth quarter of 2008, global governments announced support packages for financial institutions to mitigate the effects of the financial crisis. A potential explanation for the higher propensity for insurance sector crises in the ensuing period may be that market participants expected banking firms to benefit from these support packages more than insurance firms, and priced distress risk of the banking sector net of a higher government guarantee than distress risk in the insurance sector.

5.2.2. Lines of Insurance

The observed dynamics of insurance sector distress risk prompt the question of the distress risk associated with the different lines of insurance. To address this question, we repeat the analysis of insurance sector distress risk separately for each insurance sector: multi-line insurance, life insurance, P/C insurance, financial insurance, and reinsurance. Figure 10 shows the distress risk associated with these sectors. The left-hand panels report the distress risk in nominal price in U.S. dollars, and the right-hand panels report the distress risk in unit price relative to aggregate sector liabilities.

The insurance sectors show widely different patterns of distress risk. The nominal distress risk is low for all insurance sectors prior to the onset of the financial crisis. During the financial crisis and the European sovereign debt crisis, nominal distress risk is highest for the multi-line and life insurance sector, each averaging USD 13 billion. Nominal distress risk of the life insurance sector peaks at USD 63 billion for the week of March 13, 2009, almost twice as high as the highest level of distress risk of the multi-line insurance sector of USD 32 billion, observed for the same week. Nominal distress risk of the other insurance sectors is small in comparison and never beyond USD 6 billion throughout our sample period.

The time series of the relative distress risk tell a different story. The unit price series of the financial insurance sector begins to increase already in March 2007, several months before the unit price series of the other insurance sectors begin to trend upward in July 2007. This reflects the higher exposure of the financial insurance sector to the subprime mortgage market. During the financial crisis and European sovereign debt crisis, the financial insurance sector has the highest relative distress risk, averaging 221 basis points. The multi-line and life insurance sectors follow at a significantly lower level, each averaging 34 basis points. The ranking of the multi-line and life insurance sectors differs between the financial crisis and the European sovereign debt crisis: during the financial crisis, the life insurance sector is on average riskier; during the European sovereign debt crisis, the multi-line insurance sector is on average riskier. The P/C insurance sector has the lowest overall level of relative distress risk, averaging 12 basis points during the financial crisis and the European sovereign debt crisis.

5.3. Systemically Important Financial Institutions

In this section, we analyze the systemic importance of the individual financial institutions in our sample. We set our analyses in the global sample financial system and measure systemic risk of each firm using three distinct risk measures: marginal DIP, defined as the premium of a hypothetical insurance contract protecting the debt holders of the firm against losses during a financial crisis; CoPD, defined as the risk-neutral probability that the firm defaults during a financial crisis; and CoPSD, defined as the risk-neutral probability of a financial crisis if the firm is in distress.

We organize our discussion in three parts. We first consider the general market assessment of systemic importance of financial institutions. In a next step, we analyze the average systemic risk ranking of all firms in a given sector. Finally, we turn to the systemic risk ranking of individual financial institutions.

5.3.1. Market Assessment of Systemic Importance

All our risk measures for the systemic importance of financial institutions are derived using publicly available market data. As the following analysis confirms, the market assessment of systemic importance varies over time.

Figure 11 plots the inverse cumulative distribution function for each risk measure and year in our sample. The shape of the distribution functions varies considerably across risk measures and over time. In the years leading up to the financial crisis, the distribution functions of the marginal DIP and the CoPSD risk measures are relatively flat, indicating that financial markets only marginally discriminated between high-ranking and low-ranking financial institutions in absolute terms. In other words, financial markets did only marginally price a potential destabilizing effect of individual financial institutions. As the financial crisis unfolds, the distribution functions grow steeper, indicating that financial markets discriminate more between systemically important financial institutions and non-systemically important financial institutions. At the peak of the financial crisis and the European sovereign debt crisis, high-ranking institutions have a marginal contribution to aggregate DIP of about 3 basis points, and a CoPSD in the range of 80 to 95 percent. Low-ranking institutions during that period are associated with values close to zero in the case of the marginal DIP, and values of a few percentage points in the case of the CoPSD. Towards the end of our sample period, the distribution functions of the marginal DIP and the CoPSD begin to flatten again, indicating that individual financial institutions are less associated with systemic distress.

Two remarks on the marginal DIP and the CoPSD measure are in order. First, the CoPSD of high-ranking financial institutions consistently exceeds the unconditional PSD reported in Figure 5a. Distress of high-ranking firms therefore is clearly associated with an increased propensity of systemic distress. Second, the marginal DIP measure generally appears to discriminate more between high-ranking and medium-ranking financial institutions compared to the CoPSD measure. This is likely influenced by two aspects. The marginal DIP reflects the liability size distribution, which is heavily skewed to the right. Further, the CoPSD measure may identify a set of smaller financial institutions as *systemically as a herd*: the individual distress of an institution from this set is not sufficiently severe to trigger a financial crisis, but the collective distress of several institutions from this set may lead up to a financial crisis.[27]

Compared to the marginal DIP and the CoPSD, the distribution functions for the CoPD measure shows different dynamics. Throughout our sample period, the riskiest financial institutions are associated with a CoPD in the range of about 70 to 85 percent. Since this risk measure conditions on the occurrence of a crisis, the low time series variation in the value associated with high-ranking institutions indicates that some financial institutions are generally prone to default in times of turmoil in the broader financial system. The differentiating element then is the severity of the crisis. Indeed, during the period of the financial crisis and the European sovereign debt crisis, we observe an increase

[27]See also the discussion in Adrian and Brunnermeier (2016).

in the level of risk associated with the firms in the lower tail of the distribution. This effect recedes again towards the end of our sample period.

5.3.2. Aggregate Sector Rankings

We now consider the average ranking of all firms from a given sector. We derive the empirical ranking distributions discussed below as follows. For each week, we sort all firms in the sample global financial system according to their level of risk. Based on its ranking, we assign each firm to one of five risk buckets so that each bucket holds an identical number of firms. For each sector, we then compute the share of firms within each bucket. Figure 12 reports the time series average of the ranking distributions for our sample sectors. We organize our analysis of the sample insurers' ranking by risk measure.

Considering marginal DIP first, the ranking distributions of P/C insurers, financial insurers, and reinsurers are skewed to the right, indicating that the insurers in these sectors individually contribute only a minor share to aggregate systemic risk. The ranking distributions of multi-line insurers and life insurers, on the contrary, are skewed to the left, indicating that the insurers in these sectors individually contribute a relatively large share to aggregate systemic risk.

Under the CoPD measure, the ranking distribution of P/C insurers is again skewed to the right. The default risk of P/C insurers therefore tends to be low during turmoil in the broader financial system. The ranking distribution of financial insurers, however, is now skewed to the left. This indicates that financial insurers tend to rank among the most distressed financial institutions in times of adverse market conditions. Multi-line insurers have half of their probability mass allocated to the two highest risk buckets, and therefore also tend to have a high level of distress risk if a financial crisis occurs. Life insurers have a symmetric ranking distribution spanning all risk buckets. Reinsurers also populate all risk buckets, but tend to rank lower than life insurers.

Turning to CoPSD, the ranking distributions of P/C insurers and financial insurers are again skewed to the right. Thus, distress at the level of individual P/C insurers and financial insurers tends to be only marginally associated with financial crises. The ranking distributions of multi-line insurers and reinsurers are skewed to the left, indicating that distress at the individual level of one of these institutions tends to be associated with a financial crisis. Life insurers again have a more symmetric ranking distribution, but are also represented in the in the highest risk bucket.

5.3.3. Individual Institution Rankings

The aggregate sector rankings considered above reflect the average ranking of all firms in a given sector over time. We can apply the same methodology to identify the individual financial institutions that show the highest levels of risk. For the purpose of empirical illustration, we focus on the financial institutions represented in the two risk buckets in the upper tail of the ranking distribution of the sample global financial system.

Table 2 shows the number of firms included in these buckets, grouped by share of their respective sample period. We report the number of firms which are consistently ranking among the riskiest financial institutions (100 percent of respective sample period), very frequently ranking among the riskiest financial institutions (at least 75 percent but less than 100 percent of the respective sample period), and frequently ranking among the riskiest financial institutions (at least 50 percent but less than 75 percent of respective sample period). We further report the number of G-SIFIs among these institutions.

The first column refers to the ranking by marginal DIP. We identify ten insurers that are represented in the upper tail of the ranking distribution for at least half of their respective sample period. Nine of these insurers have been designated as G-SIIs, representing all G-SIIs included in our sample. Our methodology therefore replicates the official list of G-SIIs very closely using only publicly available market and financial statements data. All identified insurers belong to the multi-line and life insurance sectors. Two multi-line insurers consistently rank among the riskiest financial institutions. We also report the number of banks ranking among the riskiest financial institutions. The ranking by marginal DIP identifies 57 banks that are represented in the upper tail of the ranking distribution for at least half of their respective sample period, 28 of which have been designated as G-SIBs. We should note, however, that the list of banks we identify and the official list of G-SIBs are drawn from different populations: our list includes a number of banks that were either acquired or failed before the first list of G-SIBs was published.

The second column refers to the ranking by CoPD. We identify 16 insurers that are represented in the upper tail of the ranking distribution for at least half of their respective sample period. The list includes insurers from every sector except P/C insurance, providing further evidence that insurers from this sector are resilient in times of market turmoil. Seven of the identified insurers are designated as G-SIIs. Two of the identified insurers are reinsurers, which were excluded by regulators when compiling the G-SIIs lists. The remaining difference between the list of insurers we identify and the official list of G-SIIs is mostly explained by five financial insurers appearing in our ranking. Overall, the ranking by CoPD appears to be more volatile than the ranking by marginal DIP. No insurer consistently ranks among the riskiest financial institutions, and only three banks consistently rank among the riskiest financial institutions.

The third column refers to the ranking by CoPSD. We identify 13 insurers that are represented in the upper tail of the ranking distribution for at least half of their respective sample period. Four of these insurers are reinsurers, and the remaining nine insurers are from the multi-line and life insurance sectors. Seven of the nine multi-line and life insurers we identify have received G-SII status, again yielding a significant overlap between our model-based assessment approach and the official indicator-based assessment approach. One of the multi-line insurers consistently ranks among the riskiest financial institutions that we identify.

5.3.4. Discussion

Based on the results reported above, we make the following inferences on the systemic importance of insurers. We do not find evidence that insurers focusing on P/C or financial insurance contribute to systemic risk. The marginal contribution of individual insurers from these sectors is limited, and distress at the institution level is not associated with financial crises. This may be due to the fact that these insurers are individually too small to severely impair the broader financial system upon their default. P/C and financial insurers, however, differ with respect to their resilience to systemic shocks. While financial crises do not seem to affect P/C insurers, they appear to impair financial insurers. This may be explained by the type of risks underwritten by either type of insurer. Traditional P/C insurance focuses on underwriting idiosyncratic risks, which are not linked to financial markets. The financial insurers in our sample fall into two groups: financial guarantee insurers, which underwrite municipal bonds, and private mortgage insurers, which underwrite mortgage loans. Either of these risks is highly correlated with the overall state of the financial system, which exposes financial insurers to financial crises.

Several multi-line and life insurers, on the contrary, are associated with levels of systemic risk similar to the riskiest sample banks. The highest-ranking multi-line and life insurers individually contribute a significant share to aggregate systemic risk in the financial system. Moreover, distress of some multi-line and life insurers is associated with financial crises. Several factors may contribute to this finding. Multi-line and life insurers are on average larger than P/C and financial insurers by an order of magnitude. Moreover, the multi-line and life insurers in our sample include internationally active financial institutions with global exposures. Finally, the nature of the investment and funding strategies of these insurers as well as underwriting of non-traditional or non-insurance risks may give rise to strong interconnectedness with financial markets. The last point may also serve as a potential explanation for the high default risk of some multi-line and life insurers in times of turmoil in the broader financial system.

Reinsurers fall in between. They individually do not contribute a significant share to the aggregate systemic risk of the sample. However, distress of some reinsurers is associated with financial crises. Following Cummins and Weiss (2014), this may indicate that these reinsurers are interconnected within the financial system in such a way that their default impairs other financial institutions, eventually triggering a financial crisis.

5.4. Systemic Risk Determinants

In this section, we analyze the role of the credit risk parameters for our systemic risk measures. Our results confirm those obtained by Huang et al. (2012a,b) for the aggregate and marginal DIP indicator, and shed light on the sensitivities of the other measures of aggregate systemic risk and individual systemic importance that we analyze.

Table 3 examines the input factor determinants of the measures of aggregate systemic risk. We consider the aggregate DIP measure in unit price, the risk-neutral PSD, and the

ETL in unit price as the dependent variables, and focus on the explanatory power of the cross-sectional average of risk-neutral probabilities of default and asset return correlations. The results described in the following relate to the sample global financial system.[28]

The level of the risk-neutral probabilities of default is the dominant factor for the marginal DIP and the risk-neutral PSD, on its own explaining 87 and 88 percent of the respective time series variation. Asset return correlations individually explain about half of the time series variation of either measure, but their impact diminishes once the level of risk-neutral probabilities of default is included in the regression.

The level of asset return correlations is the dominant factor for the ETL, on its own explaining 92 percent of the time series variation. Risk-neutral probabilities of default individually explain 62 percent of the time series variation, but have limited additional explanatory power once asset return correlations have been considered.

Table 4 examines the input factor determinants of the measures of individual systemic importance. We consider the marginal DIP in unit price, the risk-neutral CoPD, and the risk-neutral CoPSD as the dependent variables, and include firm-level risk-neutral probabilities of default, average asset return correlations, and liability weights as explanatory variables. For each firm, we compute the average asset return correlation as the average correlation between the firm and all other firms in the sample, and the liability weight as the liability size of the firm relative to the aggregate sample liabilities. We use ordinary least squares regressions on the panel data, clustering the standard errors at the firm level to control for potential bias, as described in Petersen (2009).

The liability weight is the single most important determinant of the marginal DIP, explaining almost half of the observed variation. Correlations are the most important input factor determinant of the other two risk measures, explaining almost half the variation in the CoPD, and more than two thirds of the variation in the CoPSD. The risk measures therefore capture different aspects of systemic importance. The marginal DIP corresponds to the common too-big-to-fail paradigm (Huang et al., 2012a,b), whereas the CoPSD corresponds to the related too-interconnected-to-fail notion. The CoPD takes a microprudential perspective and assesses the impact of turmoil in the broader financial system on the individual financial institution.

Risk-neutral probabilities of default do not explain the variation in either of the risk measures well, and are only marginally statistically significant for marginal DIP. This contrasts with the role of the average risk-neutral probabilities of default for aggregate systemic risk. While the average level of risk-neutral probabilities of default in a financial system appears to be an important determinant of aggregate systemic risk, firm-level risk neutral probabilities of default are not a good predictor of the individual contribution or exposure to systemic risk.

[28] We repeated the input factor regressions in Table 3 for the banking sector and the insurance sector. The obtained results are qualitatively similar to those for the sample global financial system.

We additionally include interaction terms to capture nonlinear effects. To alleviate concerns on multicollinearity, we calculate the interaction terms from the centered variables.[29] The interaction of the liability weight with the risk-neutral probability of default and the asset return correlation has considerable additional explanatory power for the marginal DIP, and some additional explanatory power for the risk-neutral PSD. Large firms with high levels of distress risk and large firms that are highly interconnected appear most systemically risky. The interaction terms are not statistically significant for the risk-neutral CoPD. This is to be expected, as a ceteris paribus increase in the unconditional risk-neutral probability of default or the asset return correlation should have the same impact on an institution's distress risk in a financial crisis irrespective of the institution's size.

Overall, the share of explained variation remains lower for the risk-neutral CoPD and the risk-neutral CoPSD compared to the marginal DIP. This may well be due to a higher sensitivity of the CoPD and the CoPSD to the nonlinear tail interdependencies of the financial system.

6. Policy Implications and Recommendations

The results of the previous section have a number of important policy implications. These relate to the regulation of systemic risk in financial markets, and to model-based assessments of such risk. Considering the implications for the regulation of systemic risk first, we advocate that most of the regulatory effort to enhance the stability of the global financial system should be directed towards the banking sector. Throughout the sample period, the banking sector contributes most of the systemic risk in the global financial system, whereas the insurance sector only contributes a minor share. These findings do not support a generally stricter regulation of the insurance sector. We note, however, that the relative importance and systemic risk contributions of the banking and insurance sectors may well vary across regions and countries. Regulators aiming to enhance financial stability at the regional or domestic levels need to be aware that the insurance sector could play an outsized role in the respective financial markets.

While the systemic risk contribution of the insurance sector as a whole is relatively contained, some insurers individually still show levels of systemic risk on par with the riskiest banks. Our results therefore provide a preliminary affirmation that some insurers are systemically important financial institutions, and stricter regulation of these firms seems justified. The analysis of systemic risk by line of insurance points towards a significant difference in the level of systemic risk associated with different business activities. We therefore argue for activity-based rather than entity-based regulation of systemically important insurers. If we envision financial markets as a network, where the nodes repre-

[29] The maximum variance inflation factor in the regressions is 2.8.

sent the market participants and the edges represent the business activities linking those participants, activity-based regulation targets the edges of this network.

An activity-based regulation of systemic risk in insurance could take the following form: once an insurer is considered systemically important, higher capital requirements could be applied based on the individual business activities undertaken by the firm. This approach should cover both sides of the insurance balance sheet, including underwriting activity as well as investment and financing. The additional capital requirement per business activity should reflect its systemic risk contribution. Activities relating to providing insurance for idiosyncratic risks should not entail additional capital requirements whereas activities exposing insurers to financial market movements provide a case for elevated additional capital requirements, as indicated by the varying levels of distress risk associated with these lines of business. We deem this approach to provide systemically important insurers with clear incentives to reduce those business activities that contribute most to systemic risk. Furthermore, it marks a clear route for these institutions how to shed the systemic risk label by accordingly reducing upon systemically risky business activities.[30]

Our results further have several general implications for a potential future model-based assessment methodology for aggregate systemic risk and individual systemic importance.[31] We find that market-implied risk measures differed only marginally between systemically important and non-systemically important financial institutions during the pre-crisis period. With the onset of the financial crisis, the level of systemic risk associated with systemically important financial institutions increased markedly. In order to avoid procyclicality when identifying G-SIFIs, we therefore recommend ranking financial institutions relative to each other, rather than applying fixed thresholds when determining systemic importance. Moreover, we find that distinct risk measures tend to capture different aspects of systemic importance. A model-based designation of G-SIFIs should therefore be based on a set of different risk measures.

We conclude with a consideration of policy implications drawn from our analysis of the input factor determinants of aggregate systemic risk and individual systemic importance.[32] In the analysis of the determinants of aggregate systemic risk, we find that financial institutions' average risk-neutral probability of default explains most of the variation in the aggregate DIP and the risk-neutral PSD, whereas average asset return correlations explain most of the variation in the ETL. This supports the following three conclusions.

[30] We note that this approach is broadly consistent with the higher loss absorbency requirements recently proposed by the IAIS (2015); however, we here argue for a more nuanced consideration of the level of systemic risk posed by individual business activities.

[31] Indeed, the Basel Committee on Banking Supervision considers a model-based approach as an alternative to the current indicator-based approach for identifying G-SIBs. However, in BCBS (2011, p. 3) model-based approaches were still seen "at a very early stage of development". More recently, regulators stated that they may consider systemic risk metrics for setting a threshold for systemic importance in conjunction with the updated indicator-based approach for identifying G-SIIs (IAIS, 2016, p. 25).

[32] Huang et al. (2012a,b) deduce similar implications for the aggregate and marginal DIP.

First, ad hoc indicators reflecting the average level of risk-neutral probabilities of default and asset return correlations may be used to monitor the buildup of systemic risk in financial markets. In particular, the level and co-movement of CDS spreads of financial institutions may serve as a first-order approximation of the systemic risk measures we consider. Second, neither aggregate risk measure is fully explained by a linear relationship with its input factors. The level of systemic risk in financial markets additionally depends on the nonlinear dependencies between the individual financial institutions. Third, there are two levers for policy measures aiming at financial stability. The propensity and severity of systemic distress are likely best reduced by an array of measures reducing financial institutions' average default risk and de-correlating their assets.

In the analysis of the determinants of individual systemic importance, we find that the unconditional default risk of individual financial institutions does not explain the cross-sectional variation in individual systemic importance as measured by the marginal DIP and the risk-neutral CoPSD. This highlights the importance of distinguishing between microprudential and macroprudential approaches when assessing systemic importance.

7. Conclusion

How systemically important are insurers? Our analysis suggests that the insurance sector generally accounts for only a small share of the aggregate systemic risk in the global financial system. For most of the sample period, the insurance sector also appears less risky than the banking sector on a per dollar basis. However, several insurers individually show elevated levels of systemic risk and may therefore be considered systemically important financial institutions. The marginal contribution of these insurers to the aggregate systemic risk in the financial system is on par with the riskiest banks in our sample, and these firms' distress tends to be associated with systemic events.

Our results point towards a difference in the level of systemic risk associated with different types of insurance. Overall, multi-line and life insurers tend to show the highest level of systemic risk. Financial insurers are vulnerable to turmoil in the broader financial system, but do not appear to contribute to financial instability. P/C insurers consistently rank lowest and do not appear to be systemically important. The ranking of reinsurers depends on the risk metric. The marginal contributions of individual reinsurers to aggregate systemic risk are rather small; however, distress of some reinsurers is associated with a systemic crisis in the broader financial system.

We derived these stylized facts grouping the sample insurers in sectors reflecting their principal line of business. In practice, insurers will often engage in a range of activities beyond their core businesses. Our results therefore indicate the relative riskiness of different types of insurance, and support regulating systemic risk on an activity basis rather than on an entity basis. Decomposing the systemic risk posed by insurers at the entity level into marginal contributions of individual business activities and product features is an important area for further research. In particular, an interesting question is whether the high levels of systemic risk we observed for some multi-line insurers are driven by their life insurance businesses.

While P/C insurance showed the lowest overall distress risk during our sample period, future developments in this line of business need to be closely monitored. In recent years, the industry has seen increasing demand for insuring cyber risk, which may be systemic by its very nature. Security breaches affecting information technology systems can occur simultaneously across the globe, potentially giving rise to multi-billion claims by the affected corporations, institutions, or governments. This and other new risks, as well as changes in the insurance business model, will have to be taken into account when designing future methodologies for identifying and regulating G-SIIs.

A. Data Sources and Definitions

Our analysis uses data for the period from January 1, 2004, through December 31, 2014. In the following, we describe our data sources and definitions.

A.1. Credit Default Swap Spreads

CDS spreads are available from Thomson Reuters Datastream. The database offers two different data sets with end-of-day pricing information for single-name CDS contracts. The first data set is provided by CMA DataVision and covers the period running from January 1, 2003 through September 30, 2010.[33] The second data set is compiled by Thomson Reuters and initiates coverage on December 14, 2007.[34] We merge both data sets at the reference entity level, giving us a longer time series as well as a broader cross section of firms. Reference entity coverage of the merged data set increases considerably in January 2004, which marks the beginning of our sample period.

CDS contracts are quoted for a range of standardized tenors, tiers, currencies, and restructuring clauses.[35] We require 5-year senior unsecured CDS contracts as these represent the most liquid tenor and tier. For each reference entity, we retrieve daily mid-quotes for the full set of matching contracts and calculate weekly spreads as follows.

According to CMA DataVision and Thomson Reuters, spreads are only made available in the data sets if they pass a set of standardized quality assurance processes involving procedures to identify and remove outliers and otherwise doubtful data. As a further control of data quality, we exclude stale observations, setting spreads to missing if they remain constant over a period of more than twenty consecutive trading days. We then discard all quotes recorded after the reference entity experienced a credit event, and convert all remaining quotes to complete restructuring equivalents using adjustment factors provided by Markit.[36] Following this adjustment, quotes are first aggregated at the restructuring clause level taking the arithmetic average across currencies and then aggregated at the reference entity level taking the arithmetic average across restructuring clauses. We take the arithmetic average of the aggregated daily spreads to compute the weekly spreads.

[33] CMA DataVision reports observed and derived spreads. Observed spreads are calculated aggregating spread contributions received from a consortium of buy-side firms, including investment banks, hedge funds, and asset managers. When there are insufficient spread contributions to produce an entire term structure, derived spreads are calculated for the rest of the curve fitting a proprietary term structure model.

[34] Thomson Reuters reports composite spreads. These are calculated as the arithmetic average of spread contributions received from a consortium of sell-side banks. Composite spreads are only reported if contributor prices have been received.

[35] The restructuring clause determines whether restructuring constitutes a credit event, and if so, which obligations are deliverable in a restructuring event. Sorted from most restrictive (restructuring does not constitute a credit event) to least restrictive (restructuring qualifies as a credit event and any bond is deliverable), there are the following restructuring clauses: no restructuring, modified restructuring, modified-modified restructuring, and complete restructuring.

[36] Markit-provided adjustment factors have been used to covert spreads to other restructuring clauses in, e.g., Chen et al. (2014) and Schläfer and Uhrig-Homburg (2014). Our approach is further consistent with the methodology underlying Moody's Analytics' CDS-implied expected default frequency measures; see Dwyer et al. (2010).

We choose to unify restructuring clauses and to aggregate spreads over two alternatives. The first alternative is to use only contracts with a given currency and restructuring clause. However, this would markedly reduce the size of the cross section and would potentially introduce a selection bias as currency and restructuring clause preferences differ across regions. The second alternative then is to use the most liquid currency and restructuring clause for each region. This approach is usually followed in regional analyses; however, it would introduce a bias in a global setting since spreads differ systematically between restructuring clauses. Unifying restructuring clauses and aggregating spreads alleviates these concerns and results in more robustness as well as wider coverage.

A.2. Financial Statements Data

Financial statements data is available from Bloomberg. We retrieve total liabilities as well as the liability structure from the annual consolidated balance sheets. Some firms have missing or incomplete data on the Bloomberg tape. Where possible, we fill gaps in total liability data using supplementary financial information collected from investor relations websites, regulatory authorities, and exchanges. All liabilities are converted to U.S. dollars. We compute weekly portfolio weights from the annual total liabilities using linear interpolation within fiscal years.

A.3. Risk-Free Rate

We use Bloomberg-supplied zero curves to represent the risk-free rate. These are stripped from interbank rates and instruments linked to interbank rates. We use the 5-year swap-implied rate to match the tenor of the CDS contracts used in our analysis.

B. Sample Financial Firms

[TABLE 5 ABOUT HERE]

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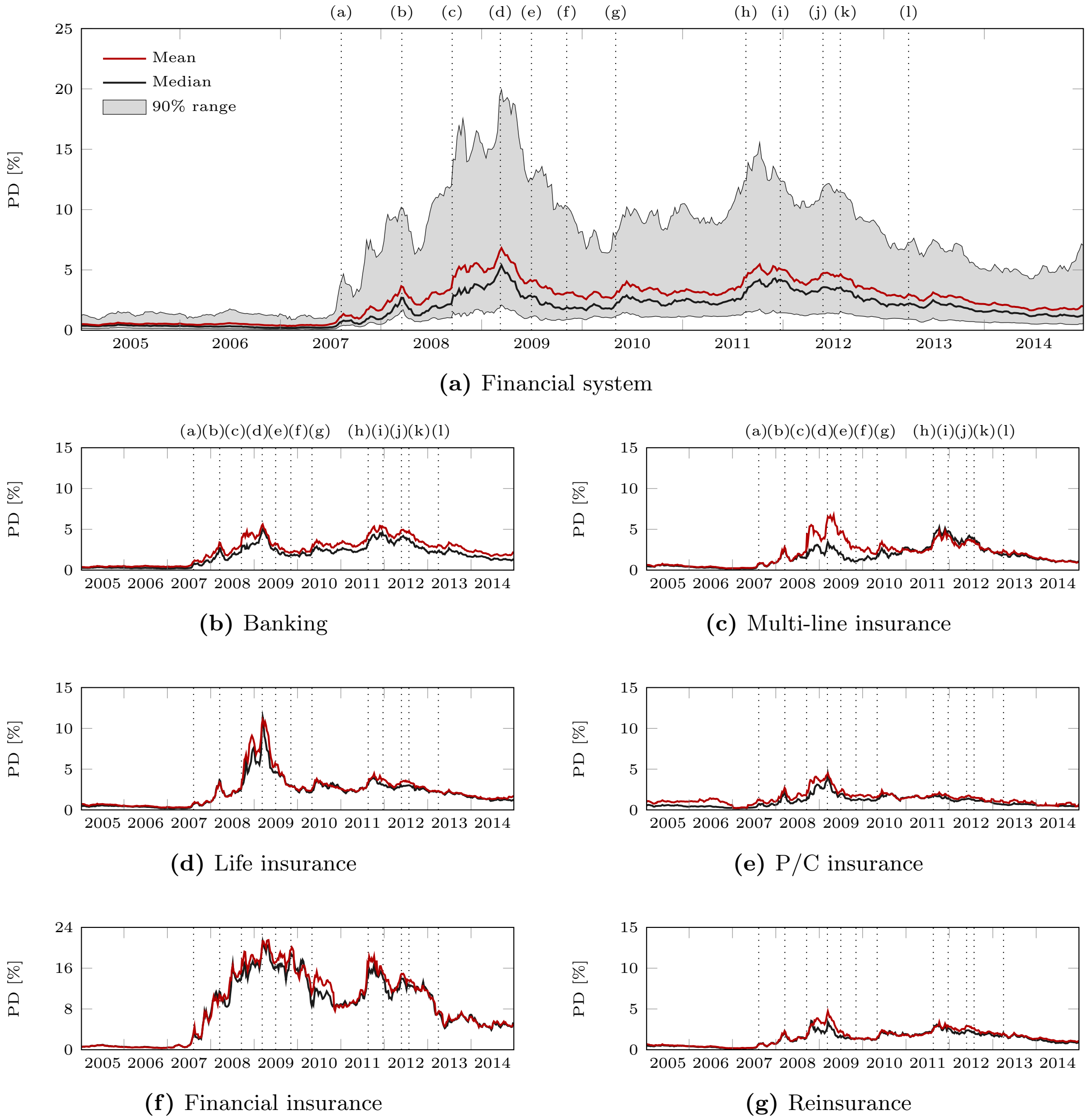


(a) Financial system

(b) Banking

(c) Multi-line insurance

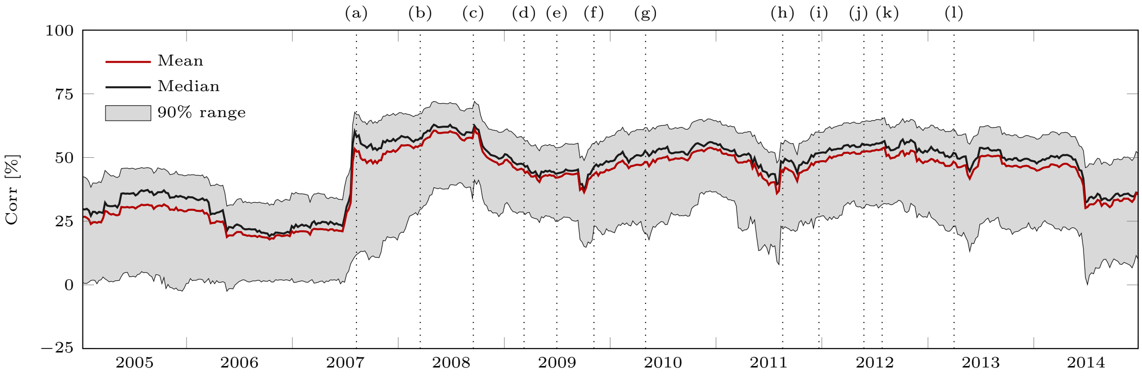
(d) Life insurance

(e) P/C insurance

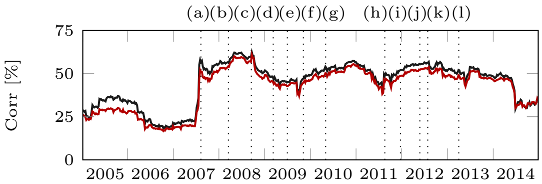
(f) Financial insurance

(g) Reinsurance

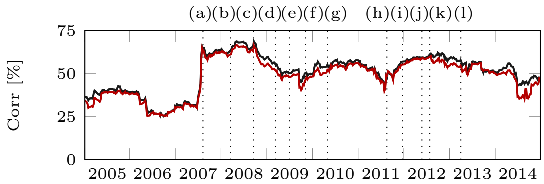
Figure 1: Probabilities of default by sector
This figure shows one-year risk-neutral probabilities of default by sector. The risk-neutral probabilities of default are calculated in weekly frequency from 5-year senior unsecured CDS spreads.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.



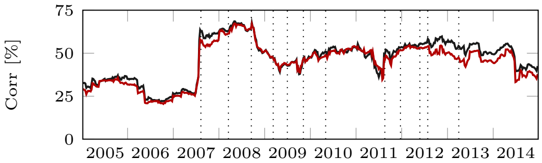
(a) Financial system



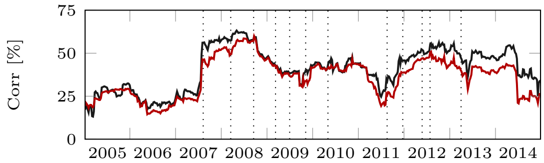
(b) Banking



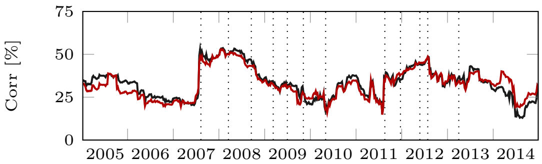
(c) Multi-line insurance



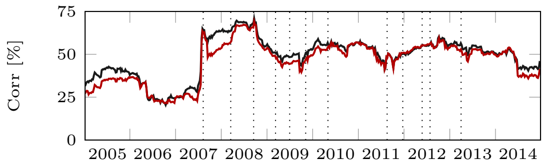
(d) Life insurance



(e) P/C insurance

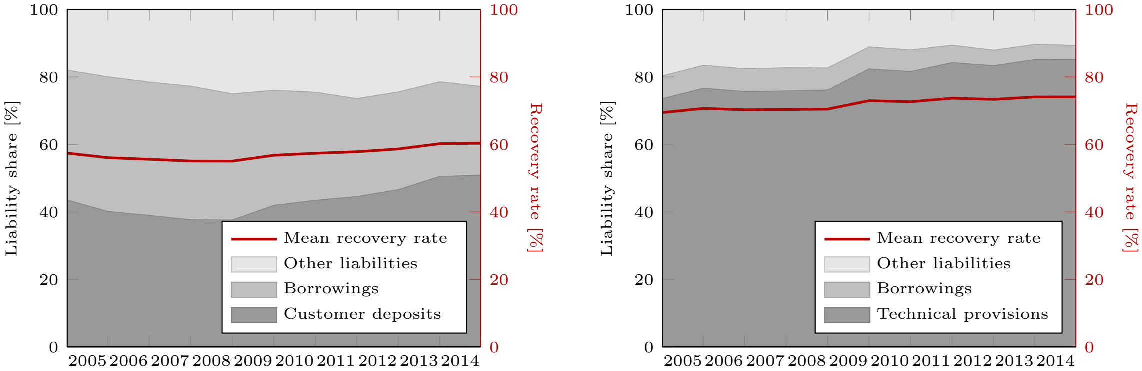


(f) Financial insurance



(g) Reinsurance

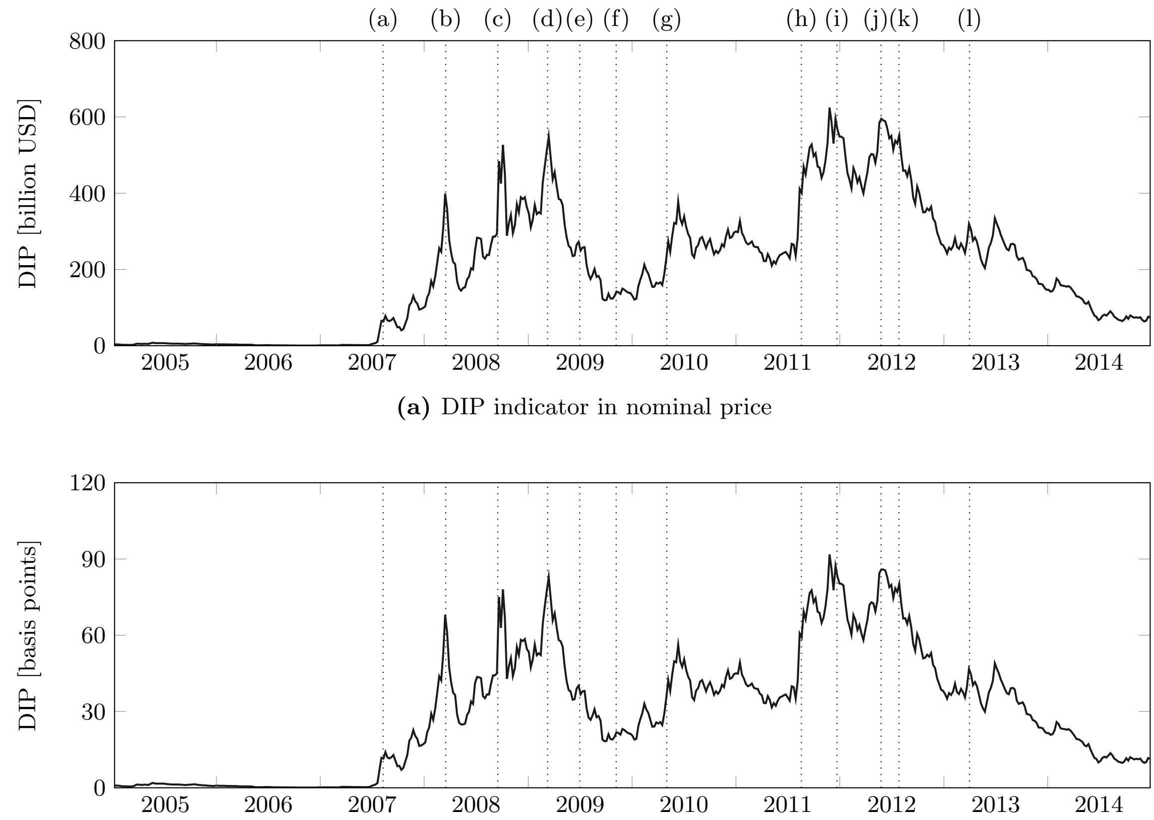
Figure 2: Asset return correlations by sector
This figure shows average asset return correlations by sector. The asset return correlations are calculated in weekly frequency from 5-year senior unsecured CDS spreads using a rolling window of one year.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.



(a) Banks

(b) Insurers

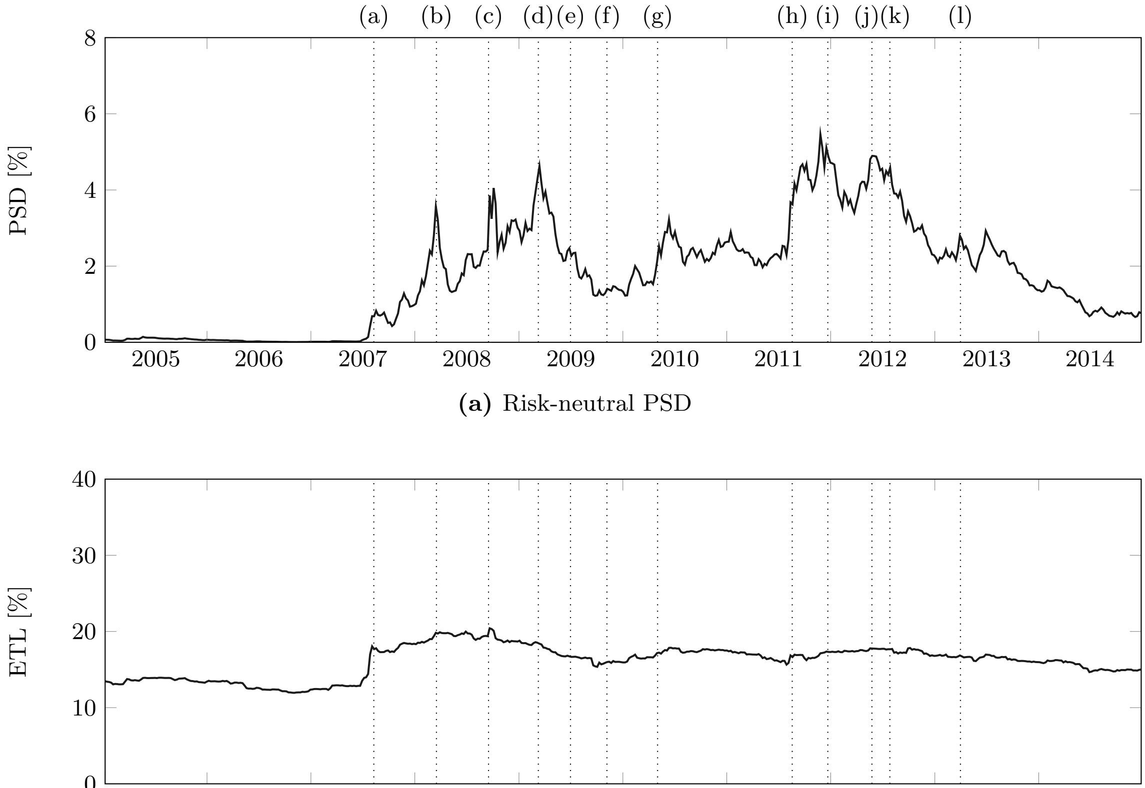
Figure 3: Liability structure and mean recovery rate
This figure shows the liability structure and mean recovery rate for the sample banking and insurance sectors. The mean recovery rate is calculated assuming a recovery rate of 80 percent for the assets invested in support of *Customer deposits* and *Technical provisions*, and a recovery rate of 40 percent for the assets invested in support of *Borrowings* and *Other liabilities*.



(a) DIP indicator in nominal price

(b) DIP indicator in unit price

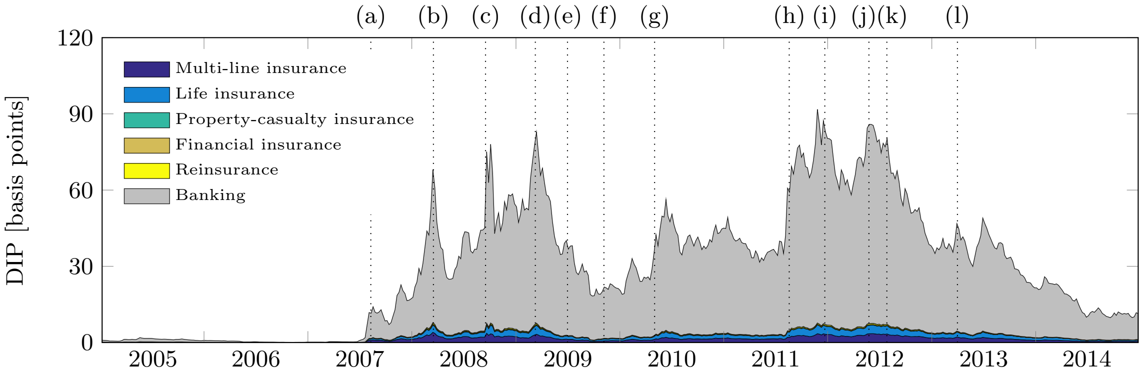
Figure 4: Systemic risk in the global financial system
This figure shows the level of systemic risk in the global financial system. Systemic risk is measured using the DIP indicator, defined as the premium of a hypothetical insurance contract protecting debt holders against systemic losses. This premium is reported in nominal price in the upper panel and in unit price relative to aggregate total liabilities in the lower panel.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.



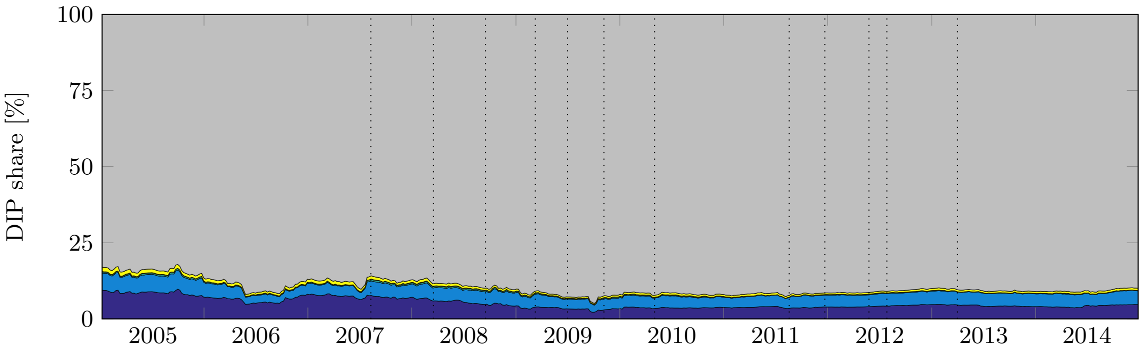
(a) Risk-neutral PSD

(b) ETL in unit price

Figure 5: Systemic risk components of the global financial system
This figure shows the systemic risk components of the global financial system. The risk-neutral PSD measures the risk-adjusted likelihood of a systemic event and is shown in the upper panel. The ETL measures the expected severity of systemic losses and is shown in unit price relative to aggregate total liabilities in the lower panel.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.

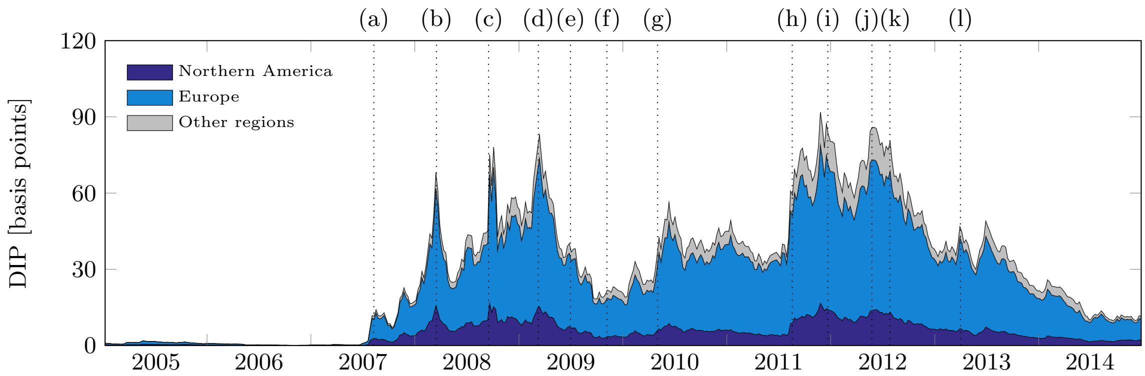


(a) DIP indicator sector contributions in unit price

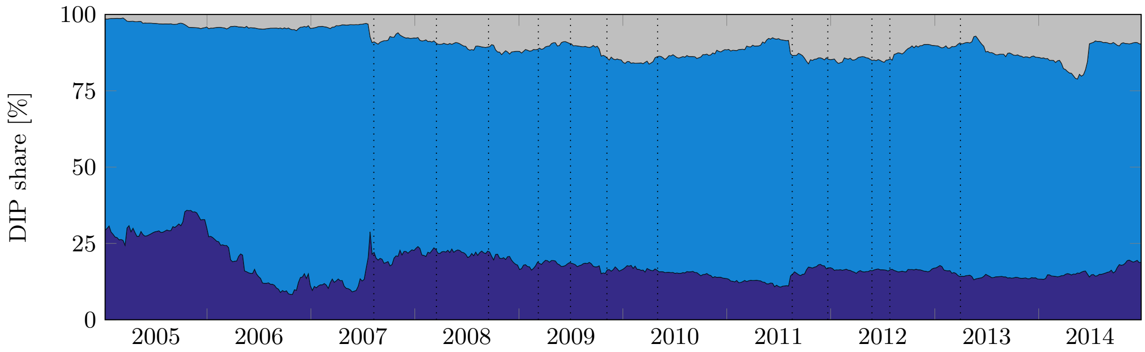


(b) DIP indicator sector contributions as share of total

Figure 6: Systemic risk in the global financial system by sector
This figure shows the level of systemic risk in the global financial system by sector. Systemic risk is measured using the DIP indicator, defined as the premium of a hypothetical insurance contract protecting debt holders against systemic losses. The sector contributions to this premium are shown in unit price in the upper panel and as share of total systemic risk in the lower panel.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.

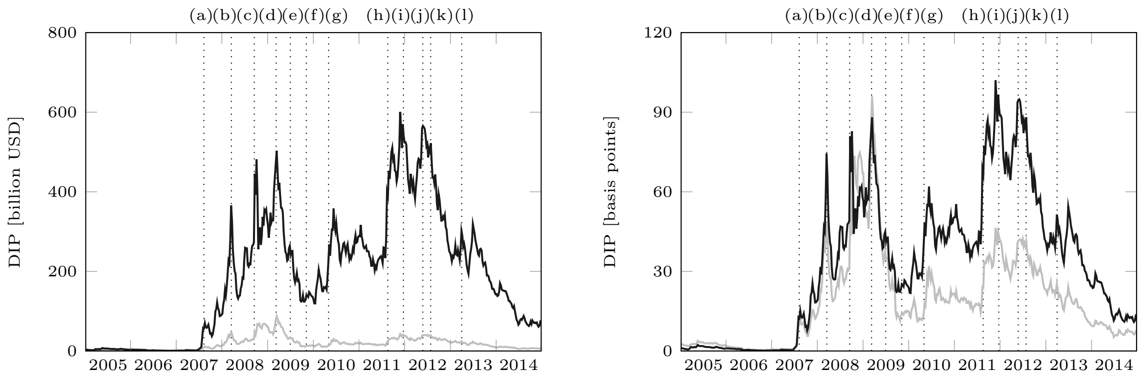


(a) DIP indicator region contributions in unit price

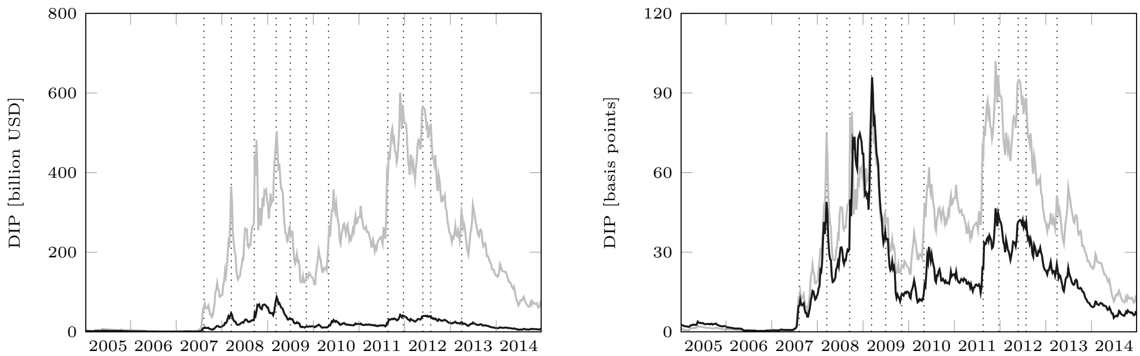


(b) DIP indicator region contributions as share of total

Figure 7: Systemic risk in the global financial system by region
This figure shows the level of systemic risk in the global financial system by region. Systemic risk is measured using the DIP indicator, defined as the premium of a hypothetical insurance contract protecting debt holders against systemic losses. The regional contributions to this premium are shown in unit price in the upper panel and as share of total systemic risk in the lower panel.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.

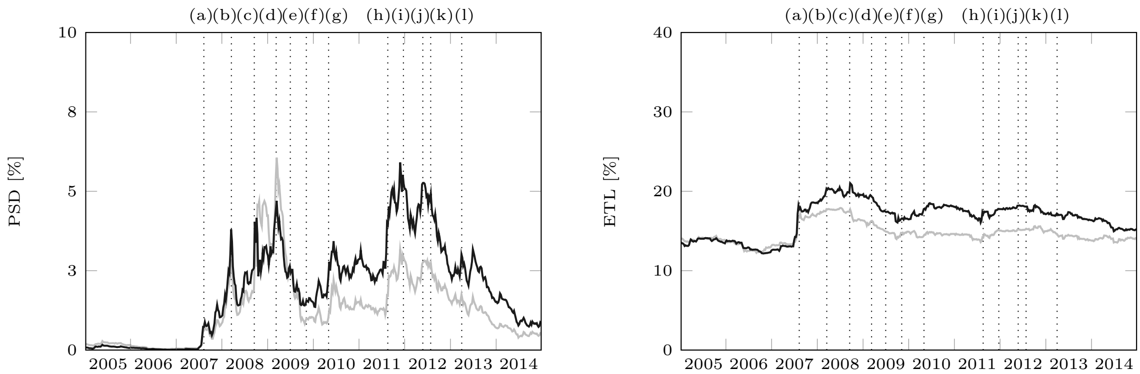


(a) Banking sector

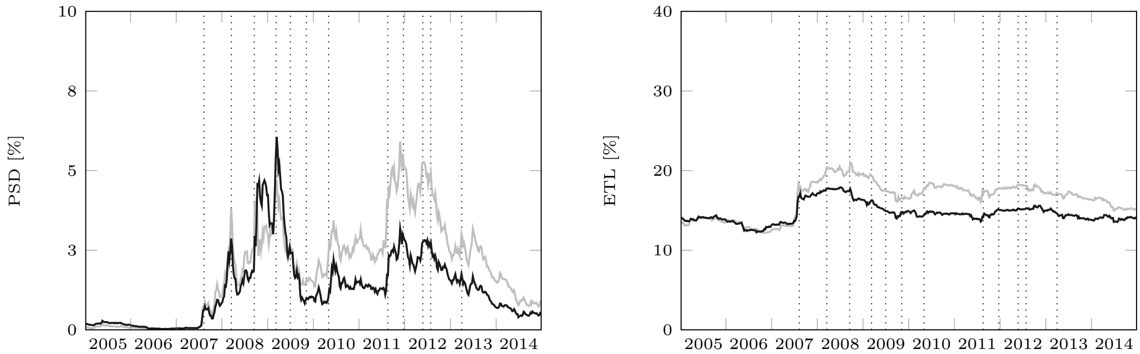


(b) Insurance sector

Figure 8: Distress risk in the global banking and insurance sector
This figure shows the level of distress risk in the global banking and insurance sector. Distress risk is measured using the DIP indicator, defined as the premium of a hypothetical insurance contract protecting debt holders against distressed losses. This premium is reported in nominal price in the left-hand panels and in unit price relative to aggregate total liabilities in the right-hand panels. The dark lines refer to the respective sector, and the light lines show the time series for the other sectors for means of comparison.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.

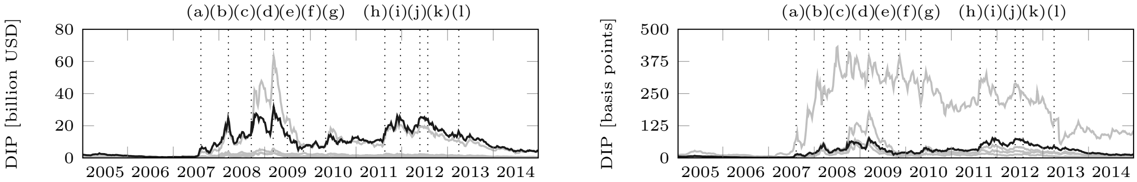


(a) Banking sector

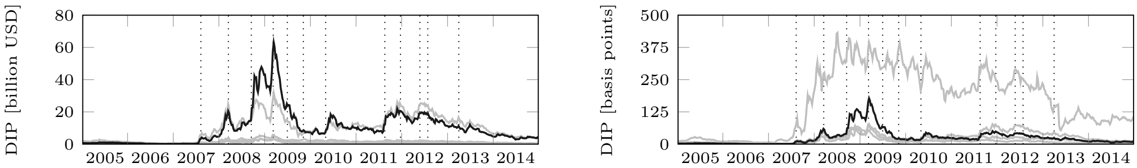


(b) Insurance sector

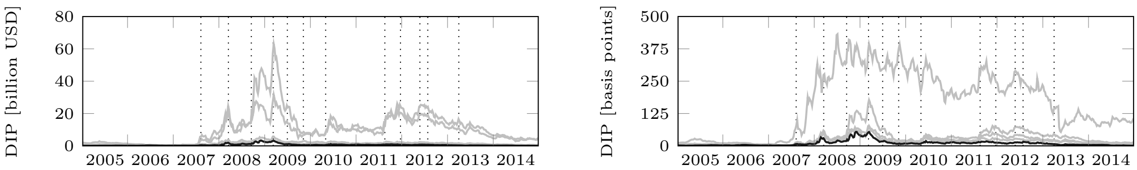
Figure 9: Distress risk components of the global banking and insurance sector
This figure shows the distress risk components of the global banking and insurance sector. The risk-neutral PSD measures the risk-adjusted likelihood of a distressed event and is shown in the left-hand panels. The ETL measures the expected severity of systemic losses and is shown in unit price relative to aggregate total liabilities in the right-hand panels. The dark lines refer to the respective sector, and the light lines show the time series for the other sectors for means of comparison.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.



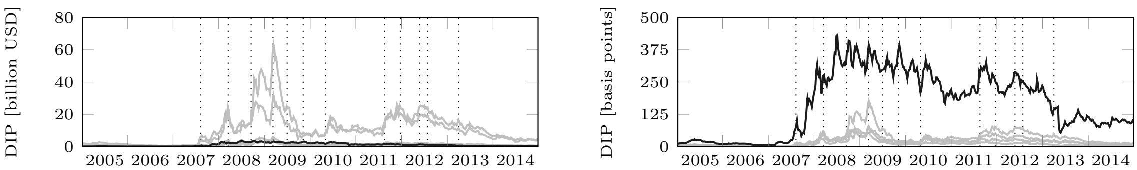
(a) Multi-line insurance



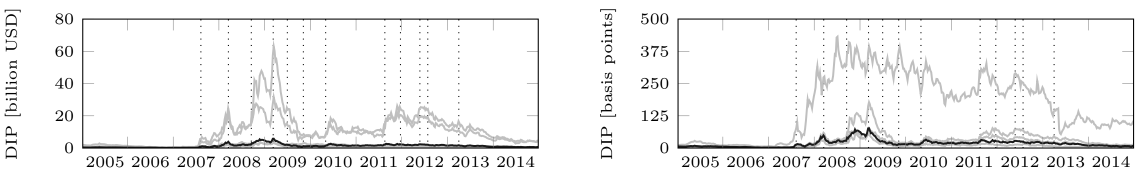
(b) Life insurance



(c) P/C insurance



(d) Financial insurance



(e) Reinsurance

Figure 10: Distress risk in the global insurance sectors
This figure shows the level of distress risk in the global insurance sectors. Distress risk is measured using the DIP indicator, defined as the premium of a hypothetical insurance contract protecting debt holders against distressed losses. This premium is reported in nominal price in the left-hand panels and in unit price relative to aggregate total liabilities in the right-hand panels. The dark lines refer to the respective sector, and the light lines show the time series for the other sectors for means of comparison.
The dotted lines mark the following events: (a) BNP Paribas funds freeze, (b) Bear Stearns takeover, (c) Lehman Brothers failure, (d) U.S. stock market low, (e) U.S. leaves recession, (f) Greek government revises budget deficit, (g) first support package for Greece agreed, (h) global stock markets fall, (i) European Central Bank conducts first round of 3-year longer-term refinancing operations, (j) Mario Draghi's "courageous leap" speech, (k) Mario Draghi's "whatever it takes" speech, (l) Eurozone leaves recession.

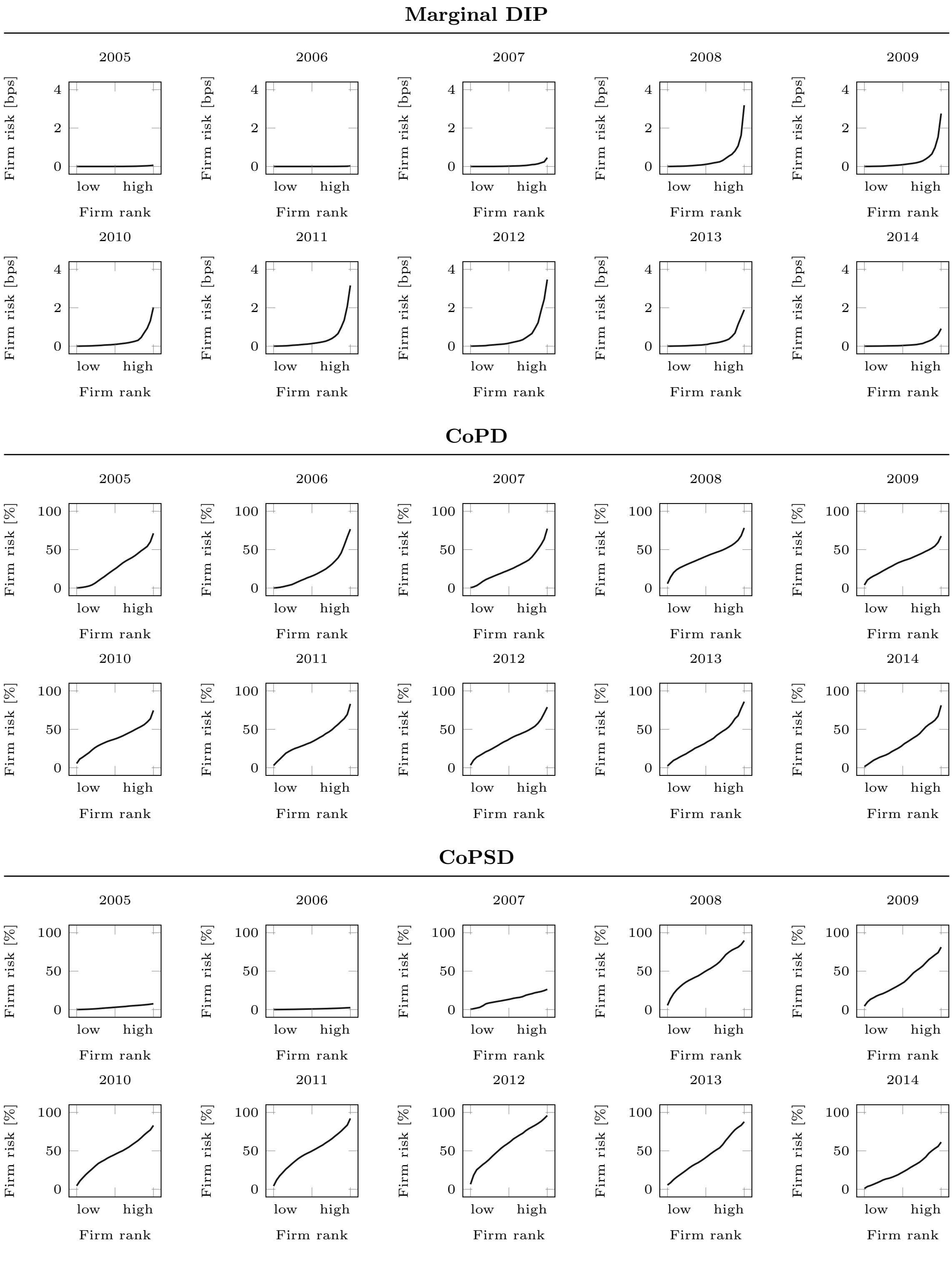


Figure 11: Inverse cumulative distribution functions for firm-level risk measures
This figure shows the inverse cumulative distribution functions of measures of firm-level risk measures. We plot yearly distribution functions for the following three risk measures: marginal DIP, defined as the premium of a hypothetical insurance contract protecting the debt holders of a firm against losses during a financial crisis; CoPD, defined as the risk-neutral probability that a firm defaults during a financial crisis; and CoPSD, defined as the risk-neutral probability of a financial crisis if a firm is in distress. The marginal DIP is expressed in unit price relative to aggregate liabilities.

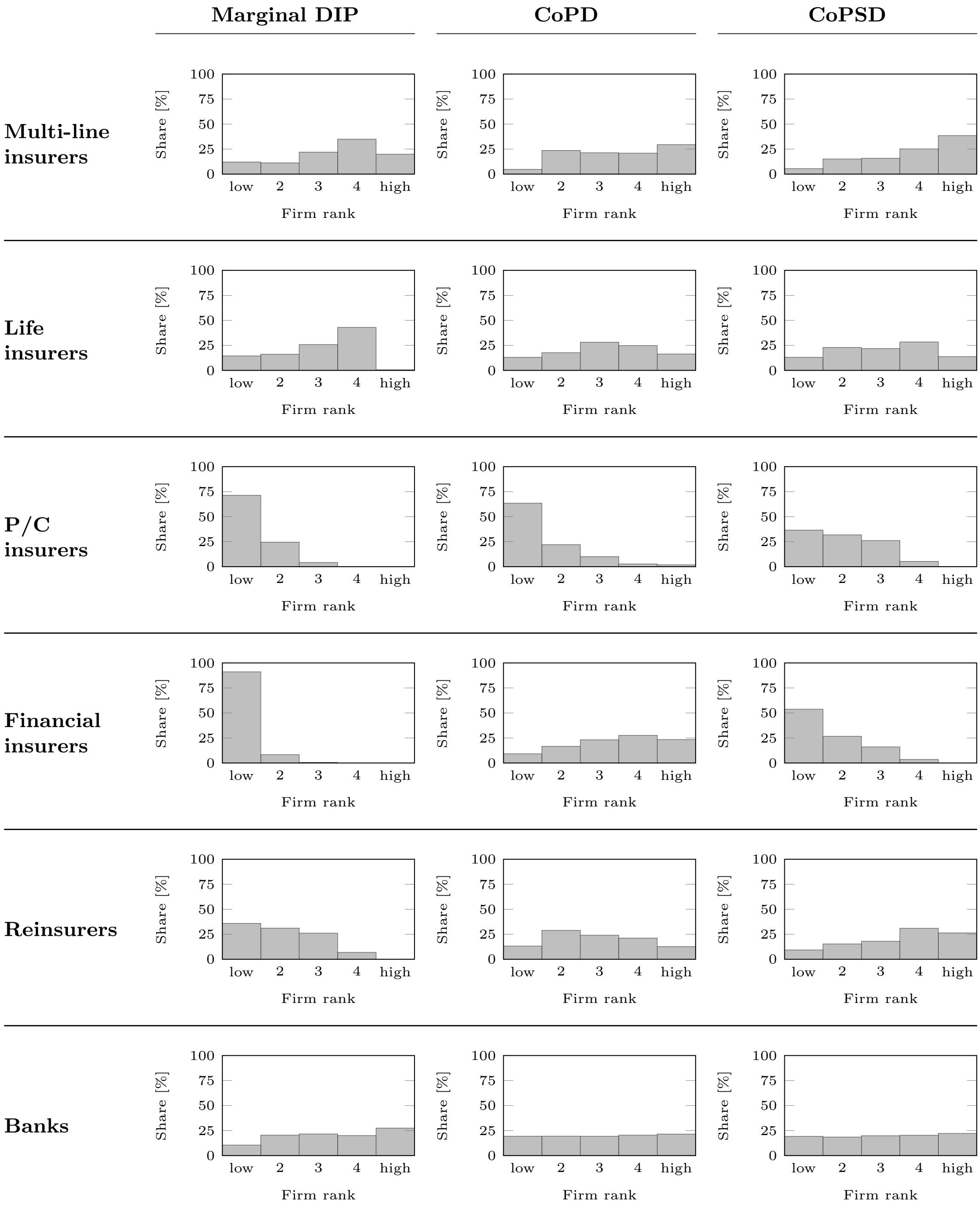


Figure 12: Firm ranking distributions by sector
This figure shows firm ranking distributions by sample sector. For each sector, the ranking distributions report the average share of firms from the sector ranking in one of five risk buckets. The ranking distributions are obtained as follows: for each week, we sort all firms in the sample global financial system according to their level of risk. Based on its ranking, we assign each firm to one of five risk buckets, each holding an identical number of firms. For each sector and week, we then compute the share of firms within each bucket. The figure reports the time series average of the sector ranking distribution for three risk measures: marginal DIP, defined as the premium of a hypothetical insurance contract protecting the debt holders of a firm against losses during a financial crisis; CoPD, defined as the risk-neutral probability that a firm defaults during a financial crisis; and CoPSD, defined as the risk-neutral probability of a financial crisis if a firm is in distress.

List of Tables

Table 1: Summary statistics

		Total liabilities[a]				CDS spreads[b]			
	N	Min	Median	Max	Sum	Sample	Period 1	Period 2	Period 3
Panel A: Full sample									
All firms	183	3	166	2,834	68,353	179	33	277	232
Panel B: Sample by sector									
Banks	133	8	211	2,834	59,035	154	28	193	227
Insurers	50	3	86	943	9,318	237	42	471	247
Multi-line ins.	8	29	459	943	3,800	130	31	218	155
Life insurers	15	21	247	548	4,044	157	36	298	166
P/C insurers	12	21	54	116	614	90	65	141	80
Financial ins.	8	3	8	23	74	882	38	1,799	984
Reinsurers	7	12	52	288	786	92	30	120	122
Panel C: Sample by region									
Northern Am.	38	3	95	1,992	11,349	320	46	647	336
Banks	12	165	1,129	1,992	8,350	151	28	264	180
Insurers	26	3	40	749	2,998	376	56	769	388
Europe	92	27	285	2,834	44,391	147	20	155	240
Banks	74	27	266	2,834	38,508	161	17	155	274
Insurers	18	29	314	943	5,883	101	27	158	124
Other regions[c]	53	8	105	1,627	12,614	135	44	220	153
Banks	47	8	115	1,627	12,177	143	47	233	162
Insurers	6	31	68	128	437	78	25	120	94

[a] Total liabilities in USD billion for 2009. Adjusted for consolidation.
[b] CDS spreads for 5-year senior unsecured contracts; expressed in basis points. We report the time series average of weekly mean spreads for the following periods: *Sample* covers the period from January 2004 through December 2014; *Period 1* covers the pre-crisis period from January 2004 through July 2007; *Period 2* covers the financial crisis and intermittent recovery from August 2007 through April 2010; *Period 3* covers the European sovereign debt crisis and subsequent recovery from May 2010 through December 2014.
[c] Latin America, Russia, the Middle East, and Asia-Pacific.

Table 2: Firms ranking among riskiest financial institutions

	Marginal DIP		CoPD		CoPSD	
	Total	G-SIFIs	Total	G-SIFIs	Total	G-SIFIs
Consistently – 100% of respective sample period						
Banks	26	19	3	1	8	5
Insurers	2	2	–	–	1	1
Multi-line ins.	2	2	–	–	1	1
Life insurers	–	–	–	–	–	–
P/C insurers	–	–	–	–	–	–
Financial ins.	–	–	–	–	–	–
Reinsurers	–	–	–	–	–	–
Very frequently – at least 75% but less than 100% of respective sample period						
Banks	20	6	29	15	21	14
Insurers	7	6	6	4	9	5
Multi-line ins.	2	2	2	2	3	2
Life insurers	5	4	2	2	3	3
P/C insurers	–	–	–	–	–	–
Financial ins.	–	–	1	–	–	–
Reinsurers	–	–	1	–	3	–
Frequently – at least 50% but less than 75% of respective sample period						
Banks	11	3	17	3	12	2
Insurers	1	1	10	3	3	1
Multi-line ins.	–	–	3	2	1	1
Life insurers	1	1	2	1	1	–
P/C insurers	–	–	–	–	–	–
Financial ins.	–	–	4	–	–	–
Reinsurers	–	–	1	–	1	–

This table shows the number of firms ranking among the riskiest financial institutions in the sample global financial system. For each week, all firms in the sample are assigned to one of five equally sized risk buckets according to their level of risk. We report the number of institutions ranking in the two highest risk buckets, grouped by share of their individual sample period spent in these buckets. We consider three risk measures: marginal DIP, defined as the premium of a hypothetical insurance contract protecting the debt holders of a firm against losses during a financial crisis; CoPD, defined as the risk-neutral probability that a firm defaults during a financial crisis; and CoPSD, defined as the risk-neutral probability of a financial crisis if a firm is in distress.

Table 3: Input factor determinants of aggregate systemic risk

Model	(1)	(2)	(3)
Panel A: Distress insurance premium (DIP)			
Constant	−6.6877***	−34.3773***	−14.1172***
	(0.4691)	(1.6573)	(0.9170)
PD	14.2502***		12.8938***
	(0.2895)		(0.4028)
Corr		1.5288***	0.2601***
		(0.0494)	(0.0365)
Adjusted R^2	0.87	0.53	0.88
Panel B: Probability of systemic distress (PSD)			
Constant	−0.3417***	−1.8917***	−0.7059***
	(0.0288)	(0.0979)	(0.0528)
PD	0.8212***		0.7547***
	(0.0177)		(0.0261)
Corr		0.0870***	0.0128***
		(0.0029)	(0.0023)
Adjusted R^2	0.88	0.52	0.88
Panel C: Expected tail loss (ETL)			
Constant	13.4610***	8.8516***	9.2671***
	(0.1095)	(0.0581)	(0.0829)
PD	1.0301***		0.2645***
	(0.0359)		(0.0265)
Corr		0.1729***	0.1469***
		(0.0016)	(0.0035)
Adjusted R^2	0.62	0.92	0.94

This table reports the results of the input factor regressions for measures of aggregate systemic risk. The dependent variables are respectively the DIP (in basis points), the risk-neutral PSD (in percentage points), and the ETL (in percentage points) of the sample global financial system. The independent variables are the cross-sectional averages of the risk-neutral probability of default (PD; in percentage points) and the asset return correlations (Corr; in percentage points).
Heteroscedasticity-consistent standard errors are given in parentheses.
Significance is indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Input factor determinants of individual systemic importance.

Model	(1)	(2)	(3)	(4)	(5)
Panel A: Marginal distress insurance premium (DIP)					
Constant	0.1984***	−0.2310***	−0.0382***	−0.3521***	−0.5016***
	(0.0278)	(0.0361)	(0.0116)	(0.0443)	(0.0220)
PD	0.0077*			0.0242***	0.1092***
	(0.0044)			(0.0049)	(0.0145)
Corr		0.0108***		0.0062***	0.0040***
		(0.0014)		(0.0008)	(0.0007)
Weight			0.3472***	0.3399***	0.4602***
			(0.0252)	(0.0247)	(0.0401)
PD × Weight					0.1617***
					(0.0209)
Corr × Weight					0.0081***
					(0.0011)
Adjusted R^2	0.00	0.13	0.45	0.53	0.87
Panel B: Conditional probability of default (CoPD)					
Constant	27.1602***	−0.5094***	28.2489***	−5.5507***	−5.4597***
	(1.2961)	(0.8561)	(1.1464)	(0.6784)	(0.8144)
PD	2.1285***			2.1011***	2.1748***
	(0.2351)			(0.1174)	(0.2268)
Corr		0.7953***		0.7036***	0.6960***
		(0.0210)		(0.0218)	(0.0258)
Weight			5.9503***	4.6723***	4.9827***
			(0.9845)	(0.7685)	(1.0751)
PD × Weight					0.1128
					(0.3346)
Corr × Weight					−0.0392
					(0.0405)
Adjusted R^2	0.13	0.46	0.08	0.59	0.59
Panel C: Conditional probability of systemic distress (CoPSD)					
Constant	29.5025***	−25.5585***	27.1832***	−28.4287***	−31.9465***
	(1.2604)	(1.6511)	(1.0837)	(1.8085)	(1.5516)
PD	1.4226***			1.0766***	3.3184***
	(0.4212)			(0.1737)	(0.4114)
Corr		1.4088***		1.3456***	1.2764***
		(0.0404)		(0.0392)	(0.0399)
Weight			8.1034***	3.6980***	7.2669***
			(0.9257)	(0.5165)	(1.2093)
PD × Weight					4.2122***
					(0.5811)
Corr × Weight					0.1250***
					(0.0475)
Adjusted R^2	0.03	0.68	0.07	0.71	0.76

This table reports the results of the input factor regressions for measures of individual systemic importance. The dependent variables are respectively the marginal DIP (in basis points), the risk-neutral CoPD (in percentage points), and the risk-neutral CoPSD (in percentage points). The independent variables are the risk-neutral probabilities of default (PD; in percentage points), asset return correlations (Corr; in percentage points), and liability weights (Weight; in percentage points). For each week, asset return correlations are calculated as the average correlation between one firm and all other firms in the sample, and liability weights are calculated as the total liabilities of the firm relative to aggregate liabilities in the sample. The dependent variables are centered when computing the interaction terms.
Heteroscedasticity-consistent standard errors clustered at the firm level (see Petersen, 2009) are given in parentheses.
Significance is indicated by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: List of sample financial firms

Firm name	Sector	Region	Country	G-SIFI
Banking firms				
AMP Bank	Banking	Asia-Pacific	Australia	no
ANZ Group	Banking	Asia-Pacific	Australia	no
Commonwealth Bank of Australia	Banking	Asia-Pacific	Australia	no
Macquarie Bank	Banking	Asia-Pacific	Australia	no
National Australia Bank	Banking	Asia-Pacific	Australia	no
St George Bank	Banking	Asia-Pacific	Australia	no
Suncorp-Metway	Banking	Asia-Pacific	Australia	no
Westpac	Banking	Asia-Pacific	Australia	no
Bank of China	Banking	Asia-Pacific	China	yes
China Development Bank	Banking	Asia-Pacific	China	no
Export-Import Bank of China	Banking	Asia-Pacific	China	no
ICBC	Banking	Asia-Pacific	China	yes
Bank of India	Banking	Asia-Pacific	India	no
Export-Import Bank of India	Banking	Asia-Pacific	India	no
ICICI Bank	Banking	Asia-Pacific	India	no
IDBI Bank	Banking	Asia-Pacific	India	no
State Bank of India	Banking	Asia-Pacific	India	no
Bank of Tokyo-Mitsubishi UFJ	Banking	Asia-Pacific	Japan	yes
Daiwa Securities Group	Banking	Asia-Pacific	Japan	no
Development Bank of Japan	Banking	Asia-Pacific	Japan	no
Mizuho Bank	Banking	Asia-Pacific	Japan	no
Nomura Holdings	Banking	Asia-Pacific	Japan	no
Sumitomo Mitsui Banking Corp	Banking	Asia-Pacific	Japan	yes
BTA Bank	Banking	Asia-Pacific	Kazakhstan	no
Halyk Savings Bank of Kazakhstan	Banking	Asia-Pacific	Kazakhstan	no
Kazkommertsbank	Banking	Asia-Pacific	Kazakhstan	no
Malayan Banking	Banking	Asia-Pacific	Malaysia	no
DBS Bank	Banking	Asia-Pacific	Singapore	no
OCBC Bank	Banking	Asia-Pacific	Singapore	no
Export-Import Bank of Korea	Banking	Asia-Pacific	South Korea	no
Hana Bank	Banking	Asia-Pacific	South Korea	no
Industrial Bank of Korea	Banking	Asia-Pacific	South Korea	no
Kookmin Bank	Banking	Asia-Pacific	South Korea	no
Korea Development Bank	Banking	Asia-Pacific	South Korea	no
Korea Exchange Bank	Banking	Asia-Pacific	South Korea	no
Shinhan Bank	Banking	Asia-Pacific	South Korea	no
Woori Bank	Banking	Asia-Pacific	South Korea	no
CTBC Financial Holding	Banking	Asia-Pacific	Taiwan	no
TMB Bank	Banking	Asia-Pacific	Thailand	no
BAWAG PSK	Banking	Europe	Austria	no
Erste Group	Banking	Europe	Austria	no
Raiffeisen Zentralbank Oesterreich	Banking	Europe	Austria	no
Fortis	Banking	Europe	Belgium	no
KBC Bank	Banking	Europe	Belgium	no
Danske Bank	Banking	Europe	Denmark	no
Banque Federative du Credit Mutuel	Banking	Europe	France	no
BNP Paribas	Banking	Europe	France	yes
Credit Agricole	Banking	Europe	France	yes
Dexia Credit Local	Banking	Europe	France	yes
Natixis	Banking	Europe	France	no
Societe Generale	Banking	Europe	France	yes
BayernLB	Banking	Europe	Germany	no
Commerzbank	Banking	Europe	Germany	yes
Deutsche Bank	Banking	Europe	Germany	yes

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Table 5 – *continued from previous page*

Firm name	Sector	Region	Country	G-SIFI
Helaba	Banking	Europe	Germany	no
HSH Nordbank	Banking	Europe	Germany	no
IKB Deutsche Industriebank	Banking	Europe	Germany	no
Landwirtschaftliche Rentenbank	Banking	Europe	Germany	no
LBBW	Banking	Europe	Germany	no
NORD/LB	Banking	Europe	Germany	no
WestLB	Banking	Europe	Germany	no
Alpha Bank	Banking	Europe	Greece	no
National Bank of Greece	Banking	Europe	Greece	no
Kaupthing Bank	Banking	Europe	Iceland	no
Landsbanki Islands	Banking	Europe	Iceland	no
Allied Irish Banks	Banking	Europe	Ireland	no
Anglo Irish Bank	Banking	Europe	Ireland	no
Bank of Ireland	Banking	Europe	Ireland	no
Banca Monte dei Paschi di Siena	Banking	Europe	Italy	no
Banca Popolare di Lodi	Banking	Europe	Italy	no
Banca Popolare di Milano	Banking	Europe	Italy	no
Banco Popolare	Banking	Europe	Italy	no
Capitalia	Banking	Europe	Italy	no
Intesa Sanpaolo	Banking	Europe	Italy	no
Mediobanca	Banking	Europe	Italy	no
SanPaolo IMI	Banking	Europe	Italy	no
UniCredit	Banking	Europe	Italy	yes
Unione di Banche Italiane	Banking	Europe	Italy	no
ABN AMRO Bank	Banking	Europe	Netherlands	no
F van Lanschot Bankiers	Banking	Europe	Netherlands	no
ING Bank	Banking	Europe	Netherlands	yes
Rabobank	Banking	Europe	Netherlands	no
SNS Bank	Banking	Europe	Netherlands	no
DNB Bank	Banking	Europe	Norway	no
Banco BPI	Banking	Europe	Portugal	no
Banco Comercial Portugues	Banking	Europe	Portugal	no
Banco Espirito Santo	Banking	Europe	Portugal	no
Caixa Geral de Depositos	Banking	Europe	Portugal	no
Banco de Sabadell	Banking	Europe	Spain	no
Banco Pastor	Banking	Europe	Spain	no
Banco Popular Espanol	Banking	Europe	Spain	no
Banco Santander	Banking	Europe	Spain	yes
Bankinter	Banking	Europe	Spain	no
BBVA	Banking	Europe	Spain	yes
Caja Madrid	Banking	Europe	Spain	no
Caja Mediterraneo	Banking	Europe	Spain	no
La Caixa	Banking	Europe	Spain	no
Nordea Bank	Banking	Europe	Sweden	yes
Skandinaviska Enskilda Banken	Banking	Europe	Sweden	no
Svenska Handelsbanken	Banking	Europe	Sweden	no
Swedbank	Banking	Europe	Sweden	no
Credit Suisse Group	Banking	Europe	Switzerland	yes
UBS	Banking	Europe	Switzerland	yes
Akbank	Banking	Europe	Turkey	no
Turkiye Is Bankasi	Banking	Europe	Turkey	no
Barclays Bank	Banking	Europe	United Kingdom	yes
HBOS	Banking	Europe	United Kingdom	no
HSBC Holdings	Banking	Europe	United Kingdom	yes
Lloyds Bank	Banking	Europe	United Kingdom	yes
Northern Rock	Banking	Europe	United Kingdom	no

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Table 5 – *continued from previous page*

Firm name	Sector	Region	Country	G-SIFI
Royal Bank of Scotland Group	Banking	Europe	United Kingdom	yes
Standard Chartered Bank	Banking	Europe	United Kingdom	yes
Yorkshire Building Society	Banking	Europe	United Kingdom	no
BNDES	Banking	Latin Am.	Brazil	no
Corp Andina de Fomento	Banking	Latin Am.	Venezuela	no
Abu Dhabi Commercial Bank	Banking	Middle East	UAE	no
National Bank of Abu Dhabi	Banking	Middle East	UAE	no
Bank of America	Banking	Northern Am.	United States	yes
Bear Stearns	Banking	Northern Am.	United States	no
Citigroup	Banking	Northern Am.	United States	yes
Goldman Sachs Group	Banking	Northern Am.	United States	yes
JPMorgan Chase	Banking	Northern Am.	United States	yes
Lehman Brothers Holdings	Banking	Northern Am.	United States	no
Merrill Lynch	Banking	Northern Am.	United States	no
Morgan Stanley	Banking	Northern Am.	United States	yes
SLM	Banking	Northern Am.	United States	no
Wachovia	Banking	Northern Am.	United States	no
Washington Mutual	Banking	Northern Am.	United States	no
Wells Fargo	Banking	Northern Am.	United States	yes
Gazprombank	Banking	Russia	Russia	no
Rosselkhozbank	Banking	Russia	Russia	no
Sberbank of Russia	Banking	Russia	Russia	no
VTB Bank	Banking	Russia	Russia	no
Insurance firms				
Ambac Financial Group	Financial ins.	Northern Am.	United States	no
Assured Guaranty Corp	Financial ins.	Northern Am.	United States	no
Assured Guaranty Municipal Corp	Financial ins.	Northern Am.	United States	no
Financial Guaranty Insurance Co	Financial ins.	Northern Am.	United States	no
MBIA	Financial ins.	Northern Am.	United States	no
MGIC Investment Corp	Financial ins.	Northern Am.	United States	no
PMI Group	Financial ins.	Northern Am.	United States	no
Radian Group	Financial ins.	Northern Am.	United States	no
Cathay Financial Holding	Life ins.	Asia-Pacific	Taiwan	no
Fubon Financial Holding	Life ins.	Asia-Pacific	Taiwan	no
Ageas	Life ins.	Europe	Belgium	no
Aegon	Life ins.	Europe	Netherlands	yes
NN Group	Life ins.	Europe	Netherlands	no
Aviva	Life ins.	Europe	United Kingdom	yes
Legal & General Group	Life ins.	Europe	United Kingdom	no
Old Mutual	Life ins.	Europe	United Kingdom	no
Prudential	Life ins.	Europe	United Kingdom	yes
Assurant	Life ins.	Northern Am.	United States	no
Genworth Holdings	Life ins.	Northern Am.	United States	no
Lincoln National	Life ins.	Northern Am.	United States	no
MetLife	Life ins.	Northern Am.	United States	yes
Prudential Financial	Life ins.	Northern Am.	United States	yes
Unum Group	Life ins.	Northern Am.	United States	no
AXA	Multi-line ins.	Europe	France	yes
Allianz	Multi-line ins.	Europe	Germany	yes
Assicurazioni Generali	Multi-line ins.	Europe	Italy	yes
Zurich Insurance Co	Multi-line ins.	Europe	Switzerland	no
RSA Insurance Group	Multi-line ins.	Europe	United Kingdom	no
AIG	Multi-line ins.	Northern Am.	United States	yes
Hartford Financial Services Group	Multi-line ins.	Northern Am.	United States	no
Liberty Mutual Group	Multi-line ins.	Northern Am.	United States	no

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Table 5 – *continued from previous page*

Firm name	Sector	Region	Country	G-SIFI
Mitsui Sumitomo Insurance Co	P/C ins.	Asia-Pacific	Japan	no
Sompo Japan Insurance	P/C ins.	Asia-Pacific	Japan	no
Tokio Marine & Nichido Fire Insurance Co	P/C ins.	Asia-Pacific	Japan	no
XLIT	P/C ins.	Europe	Ireland	no
ACE	P/C ins.	Europe	Switzerland	no
Fairfax Financial Holdings	P/C ins.	Northern Am.	Canada	no
Allstate	P/C ins.	Northern Am.	United States	no
American Financial Group	P/C ins.	Northern Am.	United States	no
Chubb	P/C ins.	Northern Am.	United States	no
Loews	P/C ins.	Northern Am.	United States	no
Safeco	P/C ins.	Northern Am.	United States	no
Travelers Cos	P/C ins.	Northern Am.	United States	no
QBE Insurance Group	Reinsurance	Asia-Pacific	Australia	no
SCOR	Reinsurance	Europe	France	no
Hannover Re	Reinsurance	Europe	Germany	no
Munich Re	Reinsurance	Europe	Germany	no
Swiss Reinsurance Co	Reinsurance	Europe	Switzerland	no
Everest Re Group	Reinsurance	Northern Am.	Bermuda	no
Berkshire Hathaway	Reinsurance	Northern Am.	United States	no

This table lists the banking and insurance firms covered in our sample. Firms are sorted alphabetically first by *Sector*, then by *Region*, then by *Country*, and finally by *Firm name*. The column *G-SIFI* indicates whether the firm (i) has been included on one of the lists of G-SIBs published by the FSB from 2011 through 2015, (ii) has been included on one of the lists of G-SIIs published by the FSB from 2013 through 2015, or (iii) operates as a principal subsidiary of one of these firms.
[a] Following the sale of its banking operations in late 2008, Fortis became a pure insurance firm that later changed its name to Ageas. We treat the firm as two different financial institutions: Fortis, referring to the period up to December 2008, and Ageas, referring to the period from January 2009 onwards.

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