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Credit and systemic risks in the financial services sector: Evidence from the 2008 global crisis

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Abstract: The Great Recession has shaken the foundations of the financial industry and led to tighter solvency monitoring of both the banking and insurance industries. To this end, we develop a portfolio credit risk model that includes firm-specific Markov-switching regimes as well as individual stochastic and endogenous recovery rates. Using weekly credit default swap premiums for 35 financial firms, we analyze the credit risk of each of these companies and their statistical linkages, placing special emphasis on the 2005–2012 period. Moreover, we study the systemic risk affecting both the banking and insurance subsectors.

Key Words: Credit risk, systemic risk, financial sector, insurance, banking, default probability, correlation, unscented kalman filter (UKF).

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1 Introduction and review of the literature

The financial crisis of 2008 highlighted serious negative consequences of the interconnectedness of large financial institutions and their increased credit risk. Indeed, the crisis demonstrated the lack of adequate credit and systemic risk monitoring within the financial services industry. In this spirit, this paper focuses mainly on credit and systemic risks affecting both insurance and banking subsectors during the 2005–2012 period.

According to Billio et al. (2012), there are four major determinants of financial crises (the so-called “L”s): leverage, losses, linkages and liquidity. It is challenging to account for the four “L”s simultaneously within a single framework. Efficient estimation procedures and realistic datasets are two noticeable limitations. In this study, we construct a multivariate credit risk model that accounts for firm-specific financial health. It captures three out of the four determinants: leverage, losses and linkages.

Various credit risk models have been proposed in the literature. They have been historically divided into two categories: structural models which link the credit events to the firm’s economic fundamentals assuming that default occurs when the firm’s value falls through some boundary, and reduced-form models which consider the surprise element of the default trigger exogenously given through a default intensity process. Even though the reduced-form approach provides a better fit to market data than the structural approach does, it lacks the economic and financial intuition of the structural framework. To overcome the limitations of both traditional approaches while retaining the main strengths of each, hybrid credit risk models have emerged in the literature.¹ In this paper, we adopt a credit risk framework that belongs to this last class of models.

Generally, studies of individual firms’ solvency have mostly focused on balance sheet information (Allen et al., 2002), credit ratings (Gupton et al., 2007), or distance to default (Bharath and Shumway, 2008). The financial services sector is no exception to the rule. Indeed, Harrington (2009) employs, among other things, balance sheet information to assess the role of AIG and the insurance subsector in the recent crisis. Milne (2014) uses the distance to default to investigate the solvency of European banks, concluding that the distance to default measure performs poorly as a market-based signal for bank risk.

Although numerous single-firm approaches exist for measuring credit risk, financial institutions are intertwined and the default of one single bank may cause a cascade of defaults that propagate to the rest of the industry. Therefore, credit risk assessment of the financial services sector also requires an examination of the interconnectedness of its institutions.

There are several ways to look at the interconnectedness of companies: correlation in the firm’s assets or default intensity through copulas and common factors (e.g. Li, 2000; Frey and McNeil, 2003; Hull et al., 2010), exposure to other common risks such as jumps (e.g. Duffie and Gârleanu, 2001) or other contagion mechanisms (e.g. Davis and Lo, 2001) such as network approaches (e.g. Nier et al., 2007; Billio et al., 2012; Markose et al., 2012).

Since the financial crisis, these multivariate credit risk frameworks have been used to investigate systemic risk in the financial sector. Notably, Huang et al. (2009) and Huang et al. (2012) construct a systemic risk measure inferred from credit default swap (CDS) spreads and equity price co-movements.² Using a network approach, principal components analysis and Granger-causality networks, Billio et al. (2012) quantify the interdependence among four groups of financial institutions during the recent crisis. Their empirical results suggest that the banking and insurance subsectors are more important sources of interconnectedness than other financial institutions. Another contribution in that field is the systemic expected shortfall proposed by Acharya et al. (2010) that measures the expected loss to each institution conditional on the undercapital-

¹For instance, Duffie and Lando (2001), Çetin et al. (2004), Giesecke and Goldberg (2003) and Giesecke (2006) use incomplete information models in a way that firm assets and the default barrier are not observable by investors. Another segment of the literature focuses on modelling the default time as the first jump of a Cox process for which the intensity depends on the firm’s fundamentals (e.g. Madan and Unal, 2000).

²Huang et al. (2009) propose the use of the so-called “distress insurance premium.” This theoretical price of insurance against distressed losses is calculated as the risk-neutral expectation of portfolio credit losses that equal or exceed a minimum share of the sector’s total liabilities.

ization of the entire financial system. Other measures of systemic risk applied to financial institutions have been proposed by Adrian and Brunnermeier (2009) and Saldías (2013).³

With respect to systemic risk in the insurance subsector, Weiß and Mühlhnickel (2014) use the Systemic Risk Index measure developed by Acharya et al. (2012) and find that the contribution of insurers to systemic risk is only determined by the insurer's size. Kessler (2014) argues that neither insurance nor reinsurance companies create significant systemic risk as long as they operate within their traditional business models. Cummins and Weiss (2014) show that non-core activities of U.S. insurers may pose systemic risk.⁴ This is found by using primary indicators of systemic risk (i.e. size of exposure, interconnectedness and lack of substitutability), along with contributing factors that increase vulnerability to systemic episodes (i.e. leverage, liquidity risks and maturity mismatches, complexity and regulation). Baluch et al. (2011) reach a similar conclusion: the insurance subsector's systemic risk is not negligible because insurers are profoundly linked with banks and insurers engage in non-core activities. Finally, Chen et al. (2014) discuss systemic risk in the insurance and banking subsectors using Huang et al. (2009)'s measure along with CDS premiums and high-frequency equity returns. They find a unidirectional causal effect from banks to insurers when accounting for heteroskedasticity.

The contributions of this paper are threefold. First, firm-specific credit risk is analyzed in the financial services sector. This requires an elaborate model that captures the main determinants of credit risk (and more specifically, financial crises). Then, sector-wide credit risk is assessed through linkages between co-movements of firm leverages. Finally, the systemic risk measures of two subsectors, namely insurance and banking, are computed and compared. These are based on the comprehensive and consistent credit risk framework presented in this paper, which is fairly different from those presented in the current systemic risk literature. Actually, other analyses commonly use proxies or raw data to reach their conclusions.

More precisely, to model the leverages, losses and linkages adequately, a regime switching extension of the multivariate hybrid credit risk model of Boudreault et al. (2014) is proposed: it allows for firm-specific statistical regimes that accommodate for changes in the leverage uncertainty, pairwise regime-dependent correlations of leverage co-movements and an endogenous stochastic recovery rate that is negatively related to the default probabilities and therefore impacts on loss distribution. Regime-switching dynamics are required to capture the various changes in behaviour through time, and more particularly during crises.

Estimation of the model's parameters is a crucial step to adequately measure both credit and systemic risks. Indeed, as defaults are rare events, a lack of direct observations brings an extra challenge when firm-specific credit risk needs to be estimated. Numerous studies construct proxies for default probabilities, recovery rates and other models' inputs based on aggregated information across ratings, balance sheet data and equity returns. More recently, a number of studies have implemented filtering approaches to deal with the latent nature of some models' variables and the presence of noise in the market data.⁵ We follow these and develop a two-stage filtering procedure extending the detection-estimation algorithm of Tugnait (1982) and the unscented Kalman filter of Julier and Uhlmann (1997). In addition to being adequate from a statistical point of view, this filter allows us to find firm-specific model parameters based on maximum likelihood estimators.

Regarding the dataset, weekly single-name CDS premiums of 35 major financial institutions over 2005–2012 are used. The use of market data is worthwhile: CDS premiums contain forward-looking information and are updated frequently by market participants as the information becomes available. Accordingly, they can better detect changes in solvency or occurrence of crises. Moreover, these are superior to rating-based methods as used by the CreditMetrics method, given that rating revisions tend to lag behind market, and rating-based probabilities of default (PDs) depend on aggregated default counts (i.e. not firm-specific).

³Adrian and Brunnermeier (2009) introduce the concept of CoVaR that measures the value at risk (VaR) of the financial system conditional on the distress of a specific firm. Saldías (2013) develops a forward-looking measure based on the gap between portfolio and average distance to default series to monitor systemic risk in Europe.

⁴Core activities refer to insurance underwriting, reserving, claims settlement and reinsurance. Non-core activities are associated with banking activities engaged in by some insurers.

⁵For instance, see Duan and Fulop (2009), Huang and Yu (2010) and Boudreault et al. (2013).

To the best of our knowledge, this study is one of the first to investigate the individual solvency of 35 financial firms during and after the crisis. In particular, we find that AIG's 1-year PD spikes to 42% on September 10, 2008, a week before its near-default. On average, the banking subsector's 1-year default probability increases by 13% during the crisis while the insurance subsector's PD increases by 11%. Our results also show a clear increase in insurers and banks' PDs during the turmoil.

Linkage varies over time. We find evidence of larger correlations between firm leverage co-movements during the high-volatility regime which suggests the existence of greater interconnectedness during the last crisis. Moreover, the regime-dependent linkage structure varies across subsectors.

Finally, as the model captures firm-specific credit risk and dependence across the firms, it serves as a building block to construct a systemic risk measure inspired from Acharya et al. (2010). We find increases in systemic risk contributions for both insurance and banking subsectors during the crisis period. In line with Chen et al. (2014), we detect a unidirectional causal effect from banks to insurers when accounting for heteroskedasticity. Therefore, even if our methodology differs and our data extends over the aftermath of the crisis, our results suggest that the direction of the causal relationship is robust. Moreover, the extended sampling period allows us to find large systemic risk measures for the banking subsector, whereas the insurance subsector's contributions are rather small during the post-crisis era. Even though Billio et al. (2012) also use a different methodology from ours, they also find an asymmetry in the degree of connectedness among banking and insurance subsectors: banks tend to have a much more significant role in the transmission of shocks.

The remainder of this paper is organized as follows: Section 2 explains the multivariate credit risk model used. In Section 3, the CDS dataset is described. The firm-specific credit risk results are discussed in Section 4. Section 5 shows the results regarding the linkages between firms. Section 6 provides an assessment of the systemic risk in both the insurance and banking subsectors. Finally, Section 7 concludes.

2 Multivariate credit risk model

As discussed in the introduction, to adequately capture credit and systemic risks requires the incorporation of some desired features, namely the "L"s of financial crises: leverage, losses, linkages, and liquidity. The model used in this study is designed to incorporate three of them:⁶ changes in the leverage, loss uncertainty and linkages. In this spirit, the proposed multivariate Markov-switching model combines the regime-switching univariate framework of Bégin et al. (2014) and the portfolio hybrid default risk approach of Boudreault et al. (2014).

2.1 Markov-switching dynamics

As a starting point to the model, time t market value of i -th firm's assets and present value of i -th firm's liabilities are denoted by $A_t^{(i)}$ and $L_t^{(i)}$ respectively. To capture changes in the asset and liabilities dynamics, a regime-switching variable is incorporated. This would allow flexibility that is needed to model periods of turmoil. Hence, $s_t^{(i)}$ is the hidden state of the regime prevailing at time t . As emphasized by the notation, the regime dynamics are firm-specific.

The leverage ratio $X_t^{(i)} = L_t^{(i)} / A_t^{(i)}$ follows a first-order two-state Markov-switching process such as

$$\log \left(X_t^{(i)} \right) = \log \left(X_{t-1}^{(i)} \right) + \left(\mu^{(i)} - \frac{1}{2} (\sigma_{s_t^{(i)}}^{(i)})^2 \right) \Delta t + \sigma_{s_t^{(i)}}^{(i)} \sqrt{\Delta t} \varepsilon_t^{(i)}, \quad i \in \{1, 2, \dots, N\} \quad (1)$$

where Δt represents the time between two consecutive observations, and $\{\varepsilon_t^{(i)}\}_{t=1}^{\infty}$ is a standardized Gaussian noise series. The drift $\mu^{(i)}$ as well as regime diffusions $\sigma_1^{(i)}$ and $\sigma_2^{(i)}$ are firm-specific parameters to be estimated.

⁶The CDS dataset used does not allow us to take into account liquidity given that only end-of-day spreads are available (aggregated across the different contributors).

When it comes to a portfolio approach, one must consider the interrelation among firms that can lead to clusters of defaults and may significantly impact the future value distribution of the portfolio. To this end, the model captures the firms' interconnections through the correlation between noise terms of log-leverage described in Equation (1), i.e.

$$\rho_{\mathbf{s}_t}^{(i,j)} = \text{Corr}^{\mathbb{P}}(\varepsilon_t^{(i)}, \varepsilon_t^{(j)}) \quad (2)$$

with $\mathbf{s}_t \in \{s_t^{(i)}, s_t^{(j)}\}$, or $\mathbf{s}_t \in \{(1,1), (1,2), (2,1), (2,2)\}$. Thus, four correlation values have to be estimated for each pair of firms depending on their specific regimes, i.e. $\rho_{\mathbf{s}_t}^{(i,j)} = (\rho_{1,1}^{(i,j)}, \rho_{1,2}^{(i,j)}, \rho_{2,1}^{(i,j)}, \rho_{2,2}^{(i,j)})$. Note that $\{s_t^{(i)} : i = 1, 2, \dots, N\}$ are independent first-order Markov chains. If $p_{11}^{(i)}$ denotes $\mathbb{P}(s_t^{(i)} = 1 \mid s_{t-1}^{(i)} = 1)$ and $p_{22}^{(i)}$ denotes $\mathbb{P}(s_t^{(i)} = 2 \mid s_{t-1}^{(i)} = 2)$, the regime state $s_t^{(i)}$ has the following transition matrix:

$$\mathbf{P}^{(i)} = \begin{bmatrix} p_{11}^{(i)} & 1 - p_{11}^{(i)} \\ 1 - p_{22}^{(i)} & p_{22}^{(i)} \end{bmatrix}. \quad (3)$$

Depending on the modelling objective, the log-leverage dynamics evolve either under risk-neutral pricing measure $\mathbb{Q}$, or under physical measure $\mathbb{P}$ for risk management purposes. The market model is incomplete, implying that there are an infinite number of pricing measures. Among these measures, we restrict the choices to those preserving the model structure by having different $\mu_t^{(i)}$, $p_{11}^{(i)}$ and $p_{22}^{(i)}$ under both measures $\mathbb{P}$ and $\mathbb{Q}$, meaning that the regime risk is priced.

2.2 Default intensity

The multivariate Markov-switching model is based on a hybrid default risk framework that combines features of both structural and reduced-form approaches. The model also features an endogenous stochastic recovery rate that depends on the firm's default probability.

More precisely, the model first relies on the assumption that default is driven by an intensity process H_t that depends on the leverage ratio X_t such that

$$H_t^{(i)} = \beta^{(i)} + \left(\frac{X_t^{(i)}}{\theta^{(i)}} \right)^{\alpha^{(i)}} \quad (4)$$

where $\alpha^{(i)} > 0$, $\beta^{(i)} > 0$ and $\theta^{(i)} > 0$ are firm-specific constants to be estimated. Furthermore, the intensity process allows the default time to be defined as a reduced-form default trigger, that is, the first jump of a Cox process:

$$\tau^{(i)} \equiv \inf \left\{ t \in \{1, 2, \dots\} : \sum_{u=0}^{t-1} H_u^{(i)} \Delta t > E_1^{(i)} \right\} \quad (5)$$

where $E_1^{(i)}$ is an independent exponential random variable with mean 1. Since $\alpha^{(i)}$, $\beta^{(i)}$ and $\theta^{(i)}$ are positive constants, the likelihood of default tends to increase with the leverage ratio. Notice that parameters α and θ gauge the sensitivity of the firm's survival against its leverage ratio. The convexity of the default intensity is guided by α , while the critical leverage threshold is defined by θ . The parameter β captures a portion of the default drivers, and ensures that H_t is a positive function when $\beta > 0$. With all other variables being the same, the larger the β , the greater the intensity and default probability.

This framework allows for an endogenous recovery rate that depends on the capital structure of the firm at the time of default. Considering liquidation and legal fees as a fraction $\kappa^{(i)}$ of the market asset value at default, the debtholders receive the smallest amount between the value of liabilities and what remains from the liquidation of assets: $\min((1 - \kappa^{(i)})A_\tau^{(i)}; L_\tau^{(i)})$. Given the leverage dynamics, the random behaviour of the recovery rate at the time of default is

$$R_\tau^{(i)} = \min \left(\left(1 - \kappa^{(i)} \right) \frac{1}{X_\tau^{(i)}}; 1 \right). \quad (6)$$

The endogenous recovery rate distribution is consistent with the empirical literature, as it is a decreasing function of the leverage ratio, meaning that default probability is negatively correlated with the recovery rate at the moment of default.⁷ The stochastic behaviour of the recovery rate as well as regime-switching dynamics imply that CDS premiums cannot be calculated in closed form. Therefore, a numerical method based on a trinomial lattice approach is used. Details on the method used to price CDSs are available from the authors on request.

3 Data and assumptions

Since the late 1990s, the credit risk market has substantially grown and the CDS has become the new instrument for investors to manage and measure their risk. Considering that the CDS premium is directly linked to the credit quality of the bond issuer, it is expected to reflect an adequate measure of credit risk. In the recent literature, many authors challenge this argument (see Friewald et al., 2012; Bielecki et al., 2011, among others). However, empirical studies suggest that credit risk is one of the most important risks involved in the CDS spread and therefore, provides a good proxy for studying a firm's credit risk.⁸ In this study, CDS premiums are used as inputs in a filtering procedure to estimate the Markov-switching hybrid credit risk model.

CDS premiums are provided by Markit for tenors of 1, 2, 3, 5, 7, and 10 years. We select the companies listed under the "Financial" classification in the database. Further selection is performed by keeping only insurance and banking firms with at least two years of data; this step is accomplished using each firm's Standard Industrial Classification (SIC) main code. This study is thus based on 35 financial sector firms.

The weekly term structure of CDS data starts on January 5, 2005, and ends on December 26, 2012, for a maximum of 417 observations. Premiums correspond to Wednesday data as it is the least likely day to be a holiday and is also less likely to be affected by weekend effects.⁹ The CDS's tier is chosen as senior and refers to the level of debt in the capital structure of the reference entities. Furthermore, the selected restructuring clause is XR, meaning that all restructuring events are excluded as trigger events.

Throughout the paper, firms might be divided into two categories: insurance firms and banking companies.¹⁰ Table 1 lists these various companies, including 16 insurance companies and 19 banking firms. The majority of these institutions are large publicly traded companies.

Figure 1 exhibits the weekly average 5-year CDS premiums for both subsectors, and the weekly average CDS term structure slope where, for a given firm, the slope is proxied by the average difference between the 10-year and 1-year CDS premiums. Among the firms, AIG, Lincoln National and Washington Mutual have the largest average premiums, reaching maximum values of 3,336.2 basis points (bps), 2,695.5 bps and 5,207.8 bps for 5-year tenors respectively. During the sample period, the market considered AIG, Lincoln National and Washington Mutual the riskiest firms. This is consistent with the near-collapse of AIG, Lincoln National's stock drop and the failure of Washington Mutual, which was the largest commercial bank failure in American history. Conversely, Fannie Mae and Freddie Mac, for which CDSs data were considered up to September 2008, have the narrowest average premiums. Although the holders of CDS triggered the default clauses for both entities, the debt was implicitly guaranteed by the U.S. government which mitigated the risk associated with these firms in the CDS market.

⁷For instance, see Altman et al. (2005).

⁸Ericsson et al. (2009), Tang and Yan (2007) and Longstaff et al. (2005) show that a significant portion of CDS spreads can be directly attributed to credit risk.

⁹For more details on the advantages of using Wednesday data, see Dumas et al. (1998).

¹⁰The range of SIC codes for insurance firms is between 6300 and 6499. The banking subsector's SIC code ranges from 6000 to 6299.

Table 1: Insurance and banking firms.

Insurance firms	Banking firms
ACE Limited (ACE)	American Express Company (AXP)
Allstate Corporation (ALL)	Bear Stearns Companies, Inc (BSC)
American International Group, Inc (AIG)	Bank of America Corporation (BACORP)
Aon Corporation (AOC)	Capital One Financial Corporation (COF)
Berkshire Hathaway, Inc (BRK)	Charles Schwab Corporation (SCH)
Chubb Corporation (CB)	Citigroup, Inc (C)
Genworth Financial, Inc (GNWTH)	Deutsche Bank AG (DB)
Hartford Financial Services Group (HIG)	Federal Home Loan Mortgage Corporation (FHLMC)
Liberty Mutual Insurance Company (LIB)	Federal National Mortgage Association (FNMA)
Lincoln National Corporation (LNC)	Goldman Sachs Group, Inc (GS)
Loews Corporation (LTR)	JPMorgan Chase & Co (JPM)
Marsh & McLennan Companies, Inc (MMC)	Lehman Bros Holdings, Inc (LEH)
MetLife, Inc (MET)	Merrill Lynch & Co, Inc (MER)
Prudential Financial, Inc (PRU)	Morgan Stanley (MWD)
Safeco Corporation (SAFC)	SunTrust Banks, Inc (STI)
XL Capital Limited (XL)	US BanCorp (USB)
	WA Mut, Inc (WM)
	Wachovia Corporation (WB)
	Wells Fargo & Co (WFC)

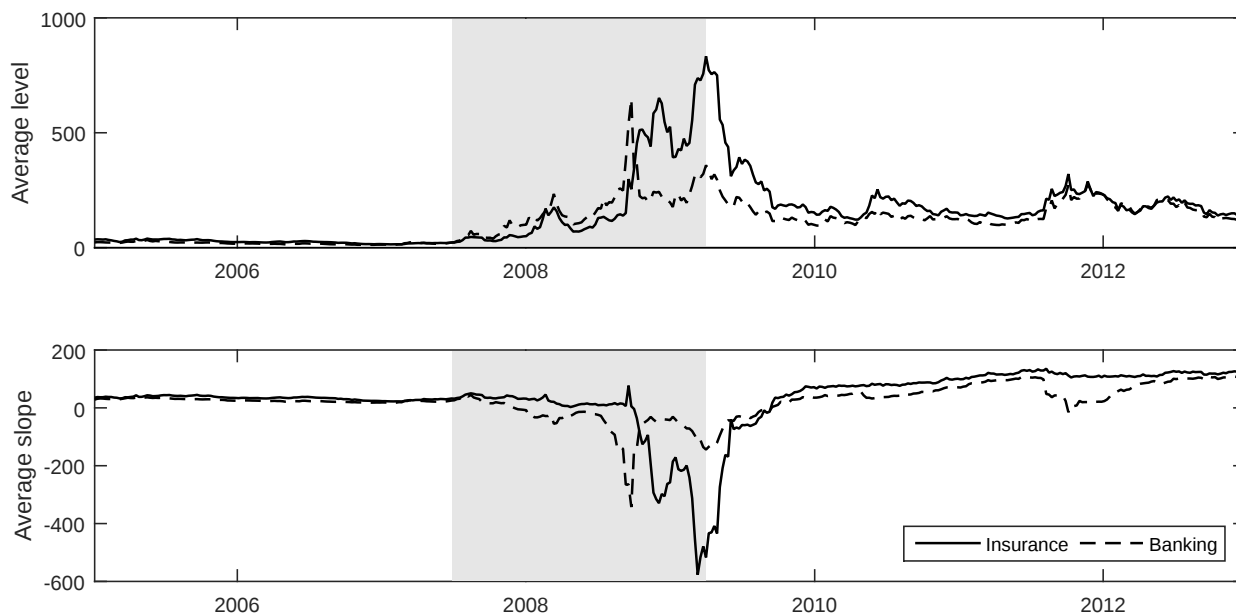


Figure 1: Evolution of the average CDS level in basis points and of the average CDS slope in basis points for both subsectors.

The CDS premiums were taken from Markit for the 16 insurance firms and 19 banking companies selected, between January 2005 and December 2012. The grey surface corresponds to the financial crisis (July 2007 to March 2009). The CDS level is proxied by the weekly average of 5-year CDS premiums. The CDS slope is proxied by the average difference between the 10-year CDS premiums and the 1-year CDS premiums.

In addition to CDS data, the model requires other inputs such as the risk-free interest rate and the firms' initial leverages. The risk-free interest rate is assumed to be constant over time at 1.75%.¹¹ The leverages as of January 2005 are approximated from the total liabilities divided by the total assets of each firm in the sample.¹²

Saunders and Allen (2010) break the recent financial crisis into three periods. The first period corresponds to the credit crisis in the mortgage market (June 2006 to June 2007), the second one covers the period of the liquidity crisis (July 2007 to August 2008), and the third the default crisis period (September 2008 to March 2009). This study focuses on the second and the third periods; thus, the financial crisis started in July 2007 and finished in March 2009 throughout this paper.

4 Firm-specific credit risk

Since leverage ratios and Markov regimes are unobservable variables, a filtering procedure is needed. We infer the latent variables from observable CDS premiums. However, estimating all firms simultaneously is not numerically feasible. The estimation is thus broken down into two stages. First, the firm-specific parameters are estimated. The second stage then focuses on the interrelation between firms while keeping the firm-specific parameters fixed. This approach is similar to the Inference Function for Margin (IFM) estimator proposed by Joe (2014). Also, an unreported Monte Carlo study shows that the two-stage approach produces unbiased estimators for all parameters.

If leverage time series were observable, the regimes could easily be filtered (for a review of classic methods, see Elliott et al., 1995). However, this is not the case and filtering regimes based on a latent time series is not straightforward. An extension of Tugnait (1982)'s detection-estimation algorithm (DEA) is designed to filter both unobserved variables simultaneously.¹³ For more information on the method, refer to Bégin et al. (2014).

The set of Markov-switching parameters to be estimated for each firm in the first stage is

$$\phi_1 = (\mu^{\mathbb{P}}, \mu^{\mathbb{Q}}, \sigma_1, \sigma_2, p_{11}^{\mathbb{P}}, p_{22}^{\mathbb{P}}, p_{11}^{\mathbb{Q}}, p_{22}^{\mathbb{Q}}, \alpha, \beta, \theta, \kappa, \delta^{(1)}, \delta^{(2)}, \delta^{(3)}, \delta^{(5)}, \delta^{(7)}, \delta^{(10)})$$

where $\delta^{(1)}$, $\delta^{(2)}$, $\delta^{(3)}$, $\delta^{(5)}$, $\delta^{(7)}$, and $\delta^{(10)}$ are standard errors of the noise terms for tenors of 1, 2, 3, 5, 7 and 10 years, respectively. The filter-based methodology allows us to recover both real probability $\mathbb{P}$ and risk-neutral $\mathbb{Q}$ parameters. Descriptive statistics of the model parameters are presented in Table 2. The interested reader can find the firm-specific parameters in Appendix C.¹⁴

Empirical results show strong persistence for both low- and high-volatility regimes. Indeed, transition probabilities $p_{11}^{\mathbb{P}}$ and $p_{22}^{\mathbb{P}}$ are greater than 87% for all firms, with the majority exceeding 97%. In particular, Fannie Mae, Freddie Mac and Merrill Lynch transition probabilities $p_{22}^{\mathbb{P}}$ reach virtually 100%, suggesting permanent regime changes during the crisis. This is because CDS data are truncated at the effective acquisition date, which corresponds to the high-volatility regime. Both the insurance and banking subsectors tend to have similar transition probabilities on average.

The average uncertainty parameters related to the first and second regimes (σ_1 and σ_2) are about 7% and 35%, respectively, implying a large difference between the two regimes. The univariate step procedure also allows the firm-specific constants α , β and θ , which define the intensity process of Equation (4), to be estimated. As shown in Appendix C, all firms have positive values for each constant. The estimated α has

¹¹This value represents the average rate of the daily 1-month and 3-month Treasury constant maturity series obtained from the Federal Reserve Bank of St. Louis (via FRED).

¹²More specifically, the firms' financial information is extracted from the Wharton Research Data Services (WRDS) Compustat database as of the fourth quarter of 2004's accounting data. In the database, the total liabilities are identified by LTQ and the total assets by ATQ.

¹³To account for nonlinearities in the state-space representation, the unscented Kalman filter (UKF) of Julier and Uhlmann (1997) is applied instead of the classic Kalman (1960) filter.

¹⁴Note that we consider the same drift parameter across both regimes in our model. Indeed, the drift parameter estimators of the latent variable are rather inaccurate and create numerical instability due to the short span of the time series used. Even in a "one-regime" framework where the log-leverage is assumed to be observed, the precision of the drift parameter estimate is proportional to the square root of the sampling period length.

Table 2: Descriptive statistics on the distribution of firm-specific parameters and noise terms.

	$\mu^Q(\%)$	$\mu^P(\%)$	σ_1	σ_2	$p_{11}^Q(\%)$	$p_{11}^P(\%)$	$p_{22}^Q(\%)$	$p_{22}^P(\%)$	κ
Average	-0.074	0.008	0.070	0.347	99.570	97.675	93.987	96.617	0.565
SD	0.169	0.261	0.015	0.015	0.194	1.699	1.663	3.222	0.065
Minimum	-0.905	-0.242	0.032	0.306	98.932	90.481	89.098	87.055	0.443
10%	-0.163	-0.136	0.054	0.328	99.338	96.146	92.328	92.082	0.475
25%	-0.073	-0.085	0.058	0.339	99.462	96.765	92.936	95.036	0.517
50%	-0.039	-0.035	0.069	0.352	99.617	98.105	93.861	97.675	0.554
75%	-0.008	0.011	0.080	0.359	99.685	98.633	95.160	99.011	0.629
90%	0.027	0.071	0.088	0.360	99.795	99.207	96.178	99.548	0.646
Maximum	0.086	1.385	0.099	0.362	99.885	99.994	96.466	99.999	0.669
Insurance									
Average	-0.027	-0.065	0.075	0.352	99.537	97.864	93.759	96.157	0.579
SD	0.058	0.082	0.014	0.010	0.150	0.992	1.823	2.483	0.065
Banking									
Average	-0.114	0.069	0.065	0.343	99.598	97.516	94.179	97.004	0.553
SD	0.219	0.338	0.014	0.017	0.224	2.138	1.539	3.758	0.065
	α	θ	$\beta(\%)$	$\delta^{(1)}$	$\delta^{(2)}$	$\delta^{(3)}$	$\delta^{(5)}$	$\delta^{(7)}$	$\delta^{(10)}$
Average	10.724	1.349	0.088	0.244	0.142	0.086	0.052	0.035	0.063
SD	2.543	0.103	0.212	0.059	0.037	0.025	0.018	0.023	0.021
Minimum	7.260	1.166	0.000	0.143	0.062	0.036	0.009	0.006	0.034
10%	8.370	1.211	0.000	0.180	0.102	0.056	0.034	0.008	0.037
25%	8.780	1.269	0.000	0.198	0.120	0.072	0.041	0.017	0.046
50%	10.191	1.346	0.022	0.237	0.140	0.083	0.050	0.037	0.062
75%	11.864	1.411	0.092	0.284	0.161	0.100	0.059	0.044	0.071
90%	15.341	1.507	0.176	0.330	0.202	0.120	0.072	0.065	0.099
Maximum	17.648	1.574	1.238	0.349	0.215	0.145	0.104	0.103	0.120
Insurance									
Average	10.148	1.365	0.057	0.251	0.136	0.084	0.043	0.032	0.059
SD	1.482	0.109	0.073	0.061	0.038	0.027	0.012	0.016	0.015
Banking									
Average	11.209	1.336	0.114	0.239	0.147	0.088	0.059	0.038	0.066
SD	3.138	0.099	0.281	0.058	0.036	0.023	0.019	0.028	0.026

[1] For each of the 35 firms, the parameters of the model are estimated using weekly CDS premiums with maturities 1, 2, 3, 5, 7 and 10 years, using the DEA-UKF filtering technique. The mean, standard deviation (SD) and quantiles are computed across firms. The last four rows compute the mean and SD across insurance and banking sectors.

[2] The δ 's represent the standard deviation of the noise terms present in the filter's observation equation.

minimum and maximum values of 7.3 and 17.7, respectively, implying that the intensity process is strongly convex with the leverage ratio. The convexity of the relationship is higher on average for banking firms when compared with insurance companies. The estimated β is generally under 1%. Finally, the critical leverage value θ lies between 1.17 and 1.57, which is realistic given that a portion of the default risk is captured by parameter β and the leverage ratio affects the default intensity in a nonlinear fashion.

Table 2 also shows the descriptive statistics of parameter κ , which is related to liquidation and legal fees. The estimated value across firms ranges between 44% and 67%, and represents a fraction of the market asset value at default.

Standard errors of the trading noise are relatively low for tenors of longer than two years with an average value lying between 3.5% and 8.6%. However, short tenors have higher variations that may be related to lower trading frequency of 1- and 2-year CDS contracts. One can also mention the very high-volatility period during which the analysis is performed, implying higher standard errors than a stable period would generate. The average standard errors are comparable across both subsectors.

Figure 2 depicts the proportion of firms in the high-volatility (turbulent) regime across both insurance and banking subsectors.¹⁵ This proportion raises rapidly at the onset of the crisis for banking firms: it goes from 21% to 84% in the first six months of the crisis, with a sizable increase in the week following the credit crunch (A). The transition for insurance companies happens later in early 2008: the proportion of firms in the high-volatility regime is virtually 100% from March 2008 to September 2008. For both subsectors, there is some persistence in the proportion during the post-crisis era. This observation is consistent with volatility regime persistence noted in Maalaoui Chun et al. (2014), Garzarelli (2009) and Mueller (2008). Interestingly, the banking subsector's proportion of firms in the high-volatility regime increases during the European debt crisis (from 2009 to 2012). For the same years, the insurance subsector's proportion remains at zero. Finally, even though the filtered statistical regimes depend only on firm-specific information, they suggest a rather important link with crises on average.

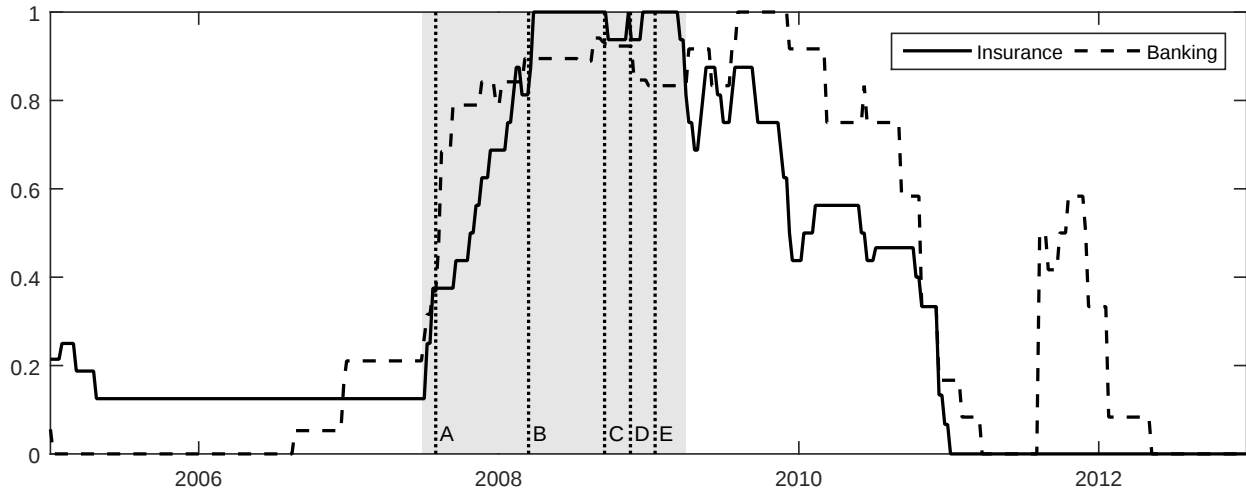


Figure 2: **Time series of the proportion of firms in the high-volatility regime across both insurance and banking subsectors.**

Based on the firm-specific parameters, the most probable regimes are extracted and aggregated across the two sectors. The different letters correspond to major events during the crisis: (A) The credit crunch begins in earnest (August 1, 2007). (B) The Federal Reserve Board approves the financing arrangement between JPM and BSC (March 14, 2008). (C) LEH files for Chapter 11 bankruptcy protection. MER is taken over by the BACORP. AIG almost defaulted the next day (September 15, 2008). (D) Three large U.S. life insurance companies seek TARP funding: LNC, HIG and GNWTH (November 17, 2008). (E) The U.S. Treasury Department, Federal Reserve, and FDIC announce a package of guarantees, liquidity access, and capital for BACORP (January 16, 2009).

4.1 Default probabilities

The evolution of PDs estimated by the model is investigated (hereafter PD_{model}). This quantity is related to the first “L” of financial crises: leverage. The credit risk framework links default probabilities to firms’ leverage ratios through the intensity process described in Equation (4). Since the firm’s leverage is not directly observable from market data, CDS premiums are used to infer the model’s latent variables (i.e. hidden regimes and leverages). Therefore, the model estimates a forward-looking measure of the firm-specific default probability.¹⁶

Throughout this subsection, we compare the model’s estimates with PDs computed using a default count approach (PD_{DC}). The latter are based on historical data rather than current market conditions. Default counts are aggregated over time by rating categories across the banking, finance and insurance industries

¹⁵ Appendix C includes the filtered regimes and the logarithm of observed CDS premiums (in basis points) for each firm, which allow the co-moving trend between time series to be observed. During the financial crisis, a large number of firms are in the high-volatility regime.

¹⁶ The model estimates are computed using the trinomial lattice approach and the estimated parameters under the physical measure $\mathbb{P}$.

from January 2002 to December 2012 in transition matrices, which can be compounded for multiple periods to produce n -year default probabilities.¹⁷ Finally, Moody's ratings, extracted for the 35 firms on a monthly basis from January 2005 to December 2012, allow us to readily obtain the PD_{DC} . Default probabilities computed using this approach are not firm-specific, but depend on aggregated information across firms with the same rating.

Below, we examine the time-varying behaviour of PD_{model} by focusing our analysis on a few important firm-specific events of the last crisis. For the sake of space, firm-specific 5-year PDs for each of the 35 firms are provided in Appendix C, while the results for AIG and LEH are given in Figure 3 and firm-specific averages across the three periods are shown in Table 3. Let us first take the case of AIG, which almost defaulted on September 16, 2008. One month prior to that date, the model derives 5-year (1-year) PD of approximately 27% (6%) for AIG. Then, the estimate reaches 34% (10%) on September 10, followed by a spike of 66% (42%) one week later. A similar behaviour is observed for Lehman Brothers prior to its collapse on September 15, 2008. Indeed, high levels are reached four months prior to the bankruptcy event (9% and 29% for the 1- and 5-year PD_{model} , respectively), followed by a jump in the probability of default of approximately 11% for all time horizons on September 10, 2008. When it comes to acquired firms such as Bear Stearns, Merrill Lynch, Wachovia and Washington Mutual, the same characteristic jump pattern is displayed close to major events preceded by relatively large PDs. Moreover, one can observe higher estimates when examining PD measures of firms that have been acquired during the crisis and distressed firms in comparison to the others in the sample.

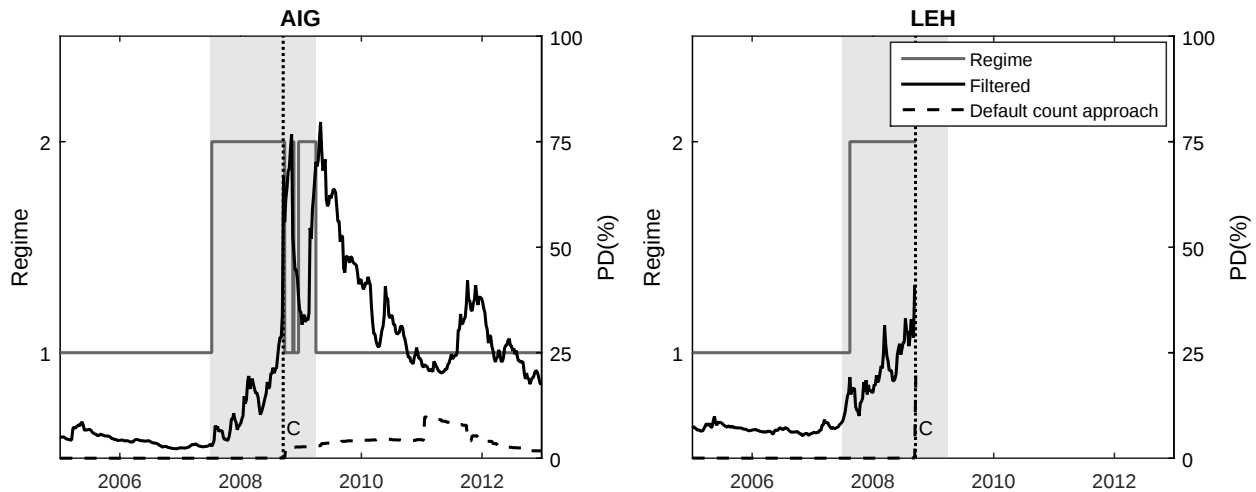


Figure 3: Five-year default probabilities computed using the credit risk model and the default count approach and filtered regimes for AIG and LEH.

This figure shows the time series of 5-year default probabilities over the period of time 2005–2012. Model's time series are inferred from CDS premiums market data. The default count approach time series are obtained from monthly transition matrices for banking, finance and insurance industries using the generator estimation approach with window length of three years ex ante default data. The letter (C) corresponds to a major event during the crisis: LEH files for Chapter 11 bankruptcy protection. MER is taken over by the BACORP. AIG almost defaulted the day after (September 15, 2008).

In opposition, PD_{DC} suffers from two main caveats. First, as it is computed using a rolling window and past data, it tends to lag behind the market, which explains why the probabilities are smaller during the crisis than in its aftermath (see Table 3). Second, it does not reflect firm-specific default probabilities, given that it is based on sector-wide aggregated data. This is another reason why many firms have the same PD_{DC} in Table 3: firms tend to have the same credit rating during that period. Contrarily, the CDS-implied default probabilities are forward looking and strongly reacts at the onset of the financial crisis and during the European crisis of 2012.

¹⁷A generator estimation approach with a window length of three years ex ante data is used. See Dionne et al. (2010) for more details.

Table 3: Descriptive statistics of five-year default probability estimates across periods.

Firm	Pre-crisis		Crisis		Post-crisis	
	Filtered	Default count	Filtered	Default count	Filtered	Default count
ACE	12.09	0.01	15.58	0.78	18.97	2.90
ALL	2.88	0.01	9.64	0.78	9.92	2.90
AXP	12.35	0.01	27.91	0.78	24.81	2.90
AIG	4.27	0.00	24.29	0.77	33.46	4.64
AOC	11.97	0.34	13.54	1.64	17.54	7.09
BSC	15.55	0.01	27.59	0.09	-	-
BRK	11.45	0.00	22.76	0.03	29.03	1.30
BACORP	10.94	0.00	20.72	0.41	30.79	3.75
COF	20.76	0.28	36.77	0.78	29.94	7.07
SCH	4.41	0.01	10.87	0.78	9.19	2.90
CB	8.17	0.01	14.70	0.78	16.11	2.90
C	7.84	0.00	21.99	0.50	29.06	3.14
DB	8.84	0.00	15.28	0.01	-	-
FHLMC	3.00	0.00	21.41	0.00	-	-
FNMA	1.90	0.00	11.09	0.00	-	-
GNWTH	15.72	0.01	41.04	1.34	48.56	7.09
GS	7.68	0.00	18.43	0.52	22.88	2.90
HIG	5.46	0.01	20.90	1.02	27.76	7.09
JPM	16.92	0.00	26.57	0.20	30.26	1.33
LEH	6.96	0.01	20.28	0.95	-	-
LIBMUT	8.10	0.34	15.16	1.64	19.04	7.09
LNC	6.49	0.01	24.54	0.81	28.08	7.09
LTR	12.33	0.27	15.73	0.78	20.14	2.90
MMC	15.84	0.33	17.38	1.64	18.97	7.09
MER	19.09	0.00	32.07	0.76	37.18	3.75
MET	4.03	0.01	17.69	0.78	24.66	2.90
MWD	20.13	0.00	35.61	0.78	39.91	3.14
PRU	4.55	0.01	21.10	0.81	24.35	7.09
SAFC	4.91	0.34	10.12	1.64	20.62	7.09
STI	4.42	0.00	16.74	0.77	22.85	7.02
USB	6.18	0.00	17.15	0.20	17.24	1.31
WM	25.09	0.01	44.67	3.25	-	-
WB	6.88	0.00	20.71	0.45	-	-
WFC	2.98	0.00	9.92	0.20	12.63	2.90
XL	11.19	0.01	30.48	1.58	28.15	9.01
Insurance	8.69	0.11	19.67	1.05	23.89	5.20
Banking	10.64	0.02	23.72	0.78	25.56	3.51

[1] This table shows descriptive statistics for 5-year default probabilities for each firm, across the different periods. Model time series are inferred from CDS premium market data. The default count approach time series are obtained from monthly transition matrices for the banking, finance and insurance industries using the generator estimation approach with a window length of three years ex ante default data.

[2] For some firms, no default probabilities are available during the post-crisis era. These are firms that either defaulted or were acquired prior to the end of the crisis.

[3] All values are reported as a percentage.

Figure 4 shows that there is a persistence of high PDs in the aftermath of the Great Financial Crisis. This figure also shows PD_{model} and PD_{DC} for 1- and 5-year horizons, averaged across both subsectors. The figure also shows various events that happened during the sampling period. Before the crisis, the average PD_{model} of both banking and insurance subsectors are at the same level. The average PD_{model} of the banking sector starts to rise just before the onset of the crisis and jumps at the credit crunch (Event A in Figure 4). The average levels of insurance subsector PD_{model} have been less affected at the beginning of the crisis, but strongly react halfway through, reaching levels higher than those of the banking subsector. Indeed, between September 3, 2008 and September 17, 2008, the insurance subsector's average PD_{model} increased by 12%, while the banking sector's average only increased by 7%. During that week (C in Figure 4), Lehman Brothers went bankrupt, Bank of America bought Merrill Lynch and the Federal Reserve Board authorized the Federal Reserve Bank of New York to lend up to \$85 billion to AIG; these events could explain this increase to some extent. Also, other insurance firms such as Genworth, Lincoln National, Hartford Financial Services and XL

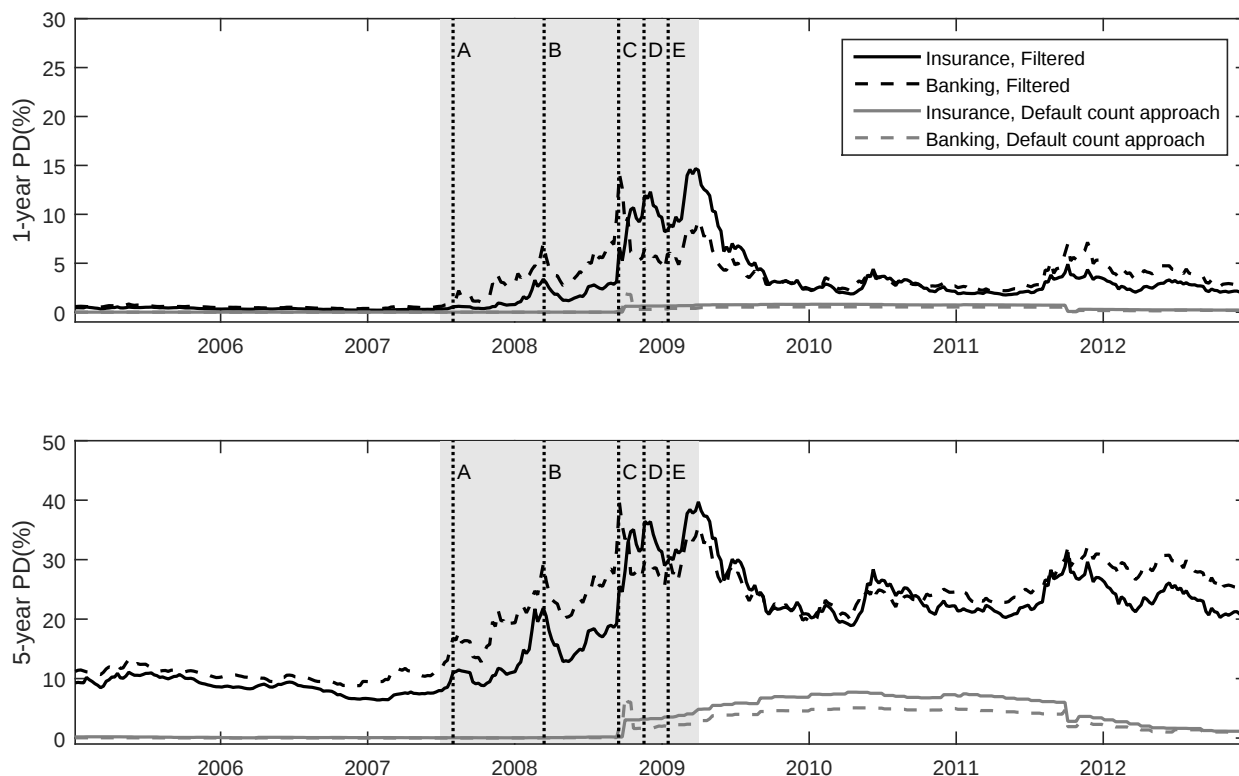


Figure 4: Average one- and five-year default probabilities computed using the credit risk model and the default count approach.

This figure shows the time series of 1- and 5-year average default probabilities across the portfolio over the 2005–2012 period. Model time series are inferred from CDS premium market data. The default count approach time series are obtained from monthly transition matrices for the banking, finance and insurance industries using the generator estimation approach with a window length of three years ex ante default data. The different letters correspond to major events during the crisis: (A) The credit crunch begins in earnest (August 1, 2007). (B) The Federal Reserve Board approves the financing arrangement between JPM and BSC (March 14, 2008). (C) LEH files for Chapter 11 bankruptcy protection. MER is taken over by the BACORP. AIG almost defaults the day after (September 15, 2008). (D) Three large U.S. life insurance companies seek TARP funding: LNC, HIG and GNWTH (November 17, 2008). (E) The U.S. Treasury Department, Federal Reserve, and FDIC announce a package of guarantees, liquidity access, and capital for BACORP (January 16, 2009).

Capital have a large PD_{model} in the second half of the crisis period.¹⁸ Note that these firms were rather compromised at the end of the crisis, bringing the average to higher levels. On November 17, 2008 (D in Figure 4), three large U.S. life insurance companies seek TARP funding; accordingly, the insurance subsector's PDs decrease for a couple of months. There is modest persistence in the aftermath of the crisis as PD_{model} slowly reverts back to a level still above that measured at the beginning of the sampling period. Then, by mid-2009, both subsectors had similar 1- and 5-year PD_{model} ; however, the banking subsector's short-term probabilities slightly increase during the European debt crisis.

On average, the insurance subsector 5-year levels of PD_{model} are lower those of the banking subsector: 2.0% in the pre-crisis era, 4.1% during the crisis, and 1.7% afterwards. Even though some insurance firms are quite exposed during the crisis (e.g. companies selling bond insurance and CDS), some are less affected by the turmoil (e.g. property and casualty insurers).

¹⁸ Average increases of 32%, 14%, 8% and 10%, respectively, from the first to the second half of the crisis period for 1-year PDs. The interested reader may refer to Appendix C for these numbers.

4.2 Recovery risk

The second “L” of financial crises is losses. It is modelled implicitly in the credit risk framework through the endogenous recovery rate of Equation (6) and depends on the firm’s financial health. Thus, the recovery rate changes over time and from one firm to another.

Figure 5 exhibits the average 1-year expected recovery rate for both subsectors. In general, the expected recovery rate is lower for insurance firms over a 1-year time horizon. The average 1-year expected rate for insurance and banking subsectors is 43.6% and 49.3%, respectively. Across both subsectors, there is a decrease in the recovery rate over time: from 54.6% in the pre-crisis era to 41.9% during the crisis, on average.

Lastly, note that the average recovery rate calculated in this study is consistent with those of Altman et al. (2005) and Vazza and Gunter (2012). Indeed, Altman et al. (2005) find an average recovery at default of 53% and 35% for senior secured and unsecured bonds, respectively. Also, in Vazza and Gunter (2012), senior secured and unsecured bonds have an average discounted recovery rate of 56.4 and 42.9%, respectively, during the 1987-2012 period.



Figure 5: Time series of the average one-year expected recovery rate for insurance and banking companies.

Based on filtered regimes, we compute the average one-year expected recovery rate each week for each firm from Equation (6). We then take the sample average across both sectors.

5 Dependence

Through the regime-dependent leverage correlation, we account explicitly for potential linkage between the various firms investigated. This dimension is important in modelling financial crises; it corresponds to Billio et al. (2012)’s third “L”.

At this point, we consider it relevant to stress that the linkage between the firms in our framework has two dimensions. In a direct manner, the correlation induces links between the firm’s leverages, and ergo, their default probabilities. This would increase the likelihood of default clusters for positively correlated firms in periods of turmoil. Also, in an indirect way, the potential losses are also correlated, as they depend on the firms’ financial health. Therefore, troubled firms that are highly linked (i.e. large positive correlation) would have recovery rates that decrease at the same time.

Below, we discuss some of the results obtained from the multivariate extension of the univariate Markov-switching framework. As a starting point to the multivariate step, suppose that we have N firms across the portfolio and correlations are recovered from leverage ratios of all possible pairs of firms (i, j) , with

$1 \leq i, j \leq N$. Thus, the number of estimated values is $N(N - 1)/2$ for each regime state leading to $2N(N - 1)$ total values. The set of parameters for the bivariate estimation stage is

$$\phi_2 = (\rho_{1,1}^{(i,j)}, \rho_{1,2}^{(i,j)}, \rho_{2,1}^{(i,j)}, \rho_{2,2}^{(i,j)})$$

for each pair of firms. Since the leverage ratio time series are inferred from the set of CDS premiums by the DEA-UKF methodology, recovering a correlation from smoothed leverage data would result in underestimated coefficients. Therefore, dependence among firms must be captured endogenously or prior to the filtering process. Details on the estimation of endogenous correlation coefficients are presented in Appendix A.

At this moment, we feel the need to stress that the estimated correlation coefficients might be larger than the levels typically seen in credit risk models. Three reasons explain these differences: the rather challenging sampling period, the fact that we use CDS premiums instead of equity returns to estimate the coefficients and an estimation technique that accounts for the presence of noise in market prices.

The heat maps of Figure 6 summarize both $\rho_{1,1}$ and $\rho_{2,2}$ for each firm.¹⁹ The results highlight positive pairwise correlations when both firms are in the same regime, with some minor exceptions for Charles Schwab and Deutsche Bank (i.e. seven coefficients out of 1,190 coefficients estimated are negative). In the stable regime (left panel), the top left 16×16 correlations suggest a higher degree of interconnectedness in the insurance subsector. Regarding the banking firms, the bottom right 19×19 coefficients display more heterogeneity. Also, Freddie Mac and Fannie Mae strongly move together, but are not significantly connected to the rest of the subsector.

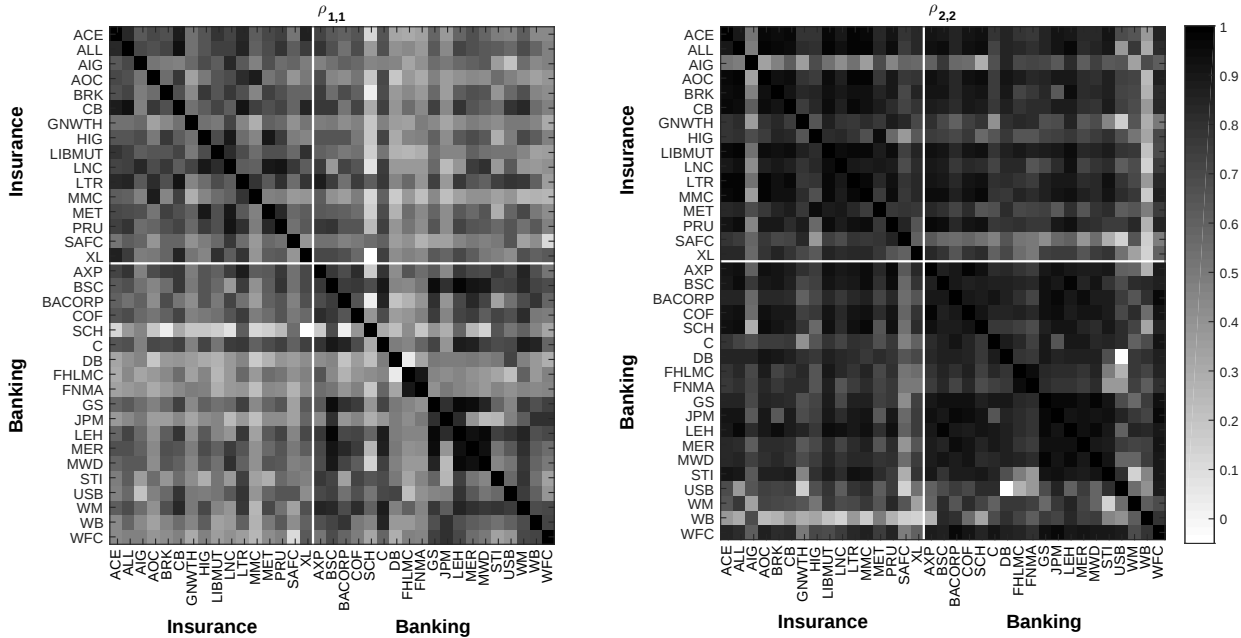


Figure 6: Heat maps of both $\rho_{1,1}$ and $\rho_{2,2}$ for the 35 firms.

This figure shows $\rho_{1,1}$ and $\rho_{2,2}$. The first 16 rows and columns correspond to the insurance subsector and last 19 ones to banks. Note that the correlation estimates are available in Appendix C.

Results also display a higher degree of leverage interdependence when the regime switches from stable to volatile regimes for both entities: accordingly, the right panel of Figure 6 (volatile regime) is much darker than the left one (stable regime).

We break the sample down into three categories: correlations between the leverages of two insurance firms (Insurance/Insurance), correlations between the leverages of two banking firms (Banking/Banking) and correlations between the leverages of one insurance firm and one banking company (Insurance/Banking).

¹⁹The interested reader can refer to the complete list of estimated pairwise correlation coefficients given in Appendix C.

Figure 7 shows the histogram of $\rho_{1,1}$ and $\rho_{2,2}$ for the three categories: Insurance/Insurance, Banking/Banking and Insurance/Banking. For the three categories, there is an increase from the stable regime average correlation to the volatile one. For correlation coefficients between two insurance firms, the average goes from 60% in the first regime to 80% in the second one, for an increase of about 20%. For banking firms' correlation coefficients, the average increase is about 26%, from 54% to 79%. As shown in Section 4, this regime is associated with the last financial crisis for most firms. The correlation between the leverages of one insurance firm and one banking company is lower in general, with averages of 45% and 74% for the stable and volatile regimes, respectively.

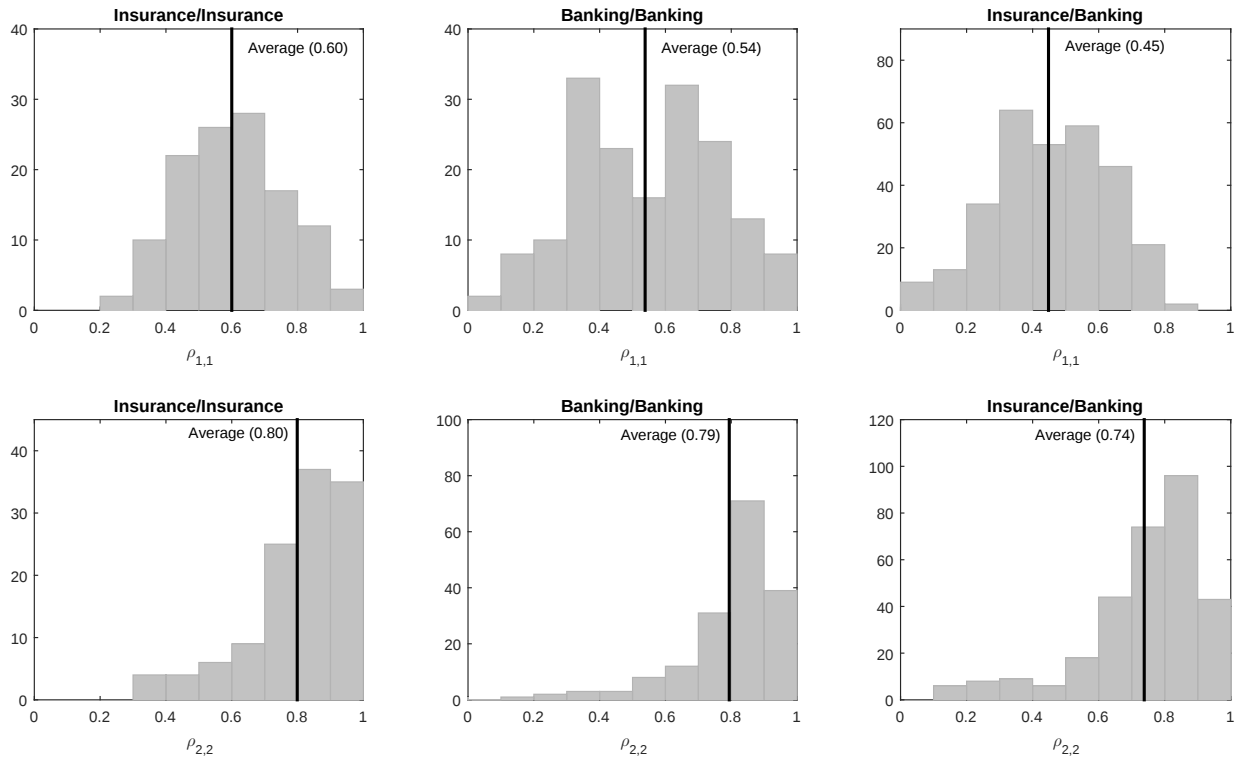


Figure 7: Histogram of $\rho_{1,1}$ and $\rho_{2,2}$ for three categories: correlations across insurance firms' leverages (Insurance/Insurance), correlations across banking companies' leverages (Banking/Banking), and correlations between insurance and banking firms' leverages (Insurance/Banking).

These figures show the empirical distribution of the $\rho_{1,1}$ and $\rho_{2,2}$ for three groups. The horizontal bar represents the sample mean. Note that the correlation estimates are available in Appendix C.

Roughly speaking, firms become much more interconnected in the high-volatility regime. Also, the general shape of the empirical distribution of correlation coefficients also changes considerably from one regime to the other.

For insurance firms (i.e. Insurance/Insurance), the stable regime correlation coefficients are distributed around its average and the empirical distribution is unimodal. For the turbulent regime, the distribution becomes left-skewed and its mode shifts to the right, meaning that the majority of insurance firms are highly correlated.

For banking firms (i.e. Banking/Banking), the low-volatility regime empirical distribution displays bimodality. This could be explained by two clusters of banking companies. The left panel of Figure 6 shows that the first-regime correlations are much more heterogeneous for financial institutions: some banks are largely correlated, while others exhibit lower levels of dependence. However, during the high-volatility regime, even firms that have low correlation in the stable regime are now highly interconnected. The empirical distribution of turbulent regime correlation coefficients is unimodal and left-skewed.

For correlation coefficients between the leverages of insurance and banking companies (i.e. Insurance/Banking), the first regime distribution displays lower correlation than the two other categories. However, during the turbulent regime, correlation increases and the distribution is also left-skewed. Interestingly, this would mean that firms less interconnected in the stable regime could be highly correlated in the turbulent one.

Figure 8 exhibits the time series of median leverage correlation coefficients across firms and for the three categories of subsectors.²⁰ As expected, the median correlation increases during the crisis, and decreases afterwards. Over 2005–2012, the banking subsector’s correlations are larger, with a median about 3% higher than the insurance subsector correlations on average. The Insurance/Insurance and Banking/Banking curves are similar in the pre-crisis era. However, at the onset of the crisis, the Banking/Banking median correlation increases rapidly as the Insurance/Insurance curve remains somewhat similar. Then, at the beginning of 2008, the Insurance/Insurance median correlation coefficient starts rising as the crisis becomes much more systemic. Note that there is some persistence in the post-crisis era for the three time series.

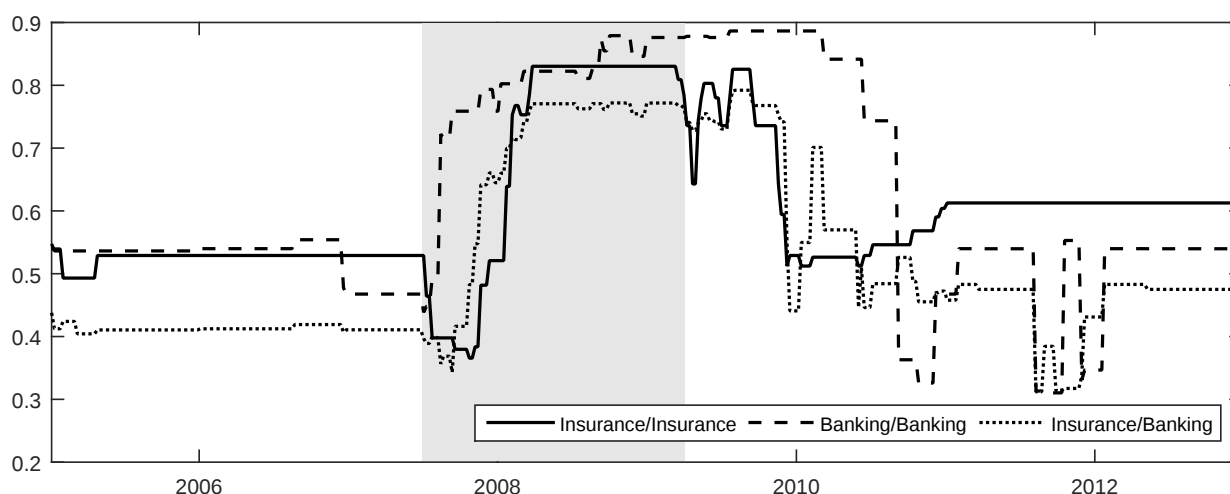


Figure 8: Time series of median leverage correlation coefficients for three groups: correlations across insurance firms (Insurance/Insurance), correlations across banking companies (Banking/Banking), and correlations between insurance and banking firms (Insurance/Banking).

Based on filtered regimes, we compute the median correlation coefficients across the three groups.

In summary, empirical results show that firms’ leverages are more correlated during the high-volatility regime, suggesting more dependence within both subsectors during the last crisis. These results present major implications for risk management practices since the increased dependence could lead to important consequences in credit-sensitive portfolios. They would also have a major impact on systemic risk measures.

6 Systemic risk

The model of Section 2 coupled with estimated parameters of Sections 4 and 5 is able to adequately grasp the systemic risk embedded in the financial services firms, as it was carefully constructed to capture three of Billio et al. (2012)’s “L”s: leverage, loss and linkage. In this study, the systemic risk measure is defined as the expected value of a loss over a period of three months given that it is higher than the 99th percentile of the loss distribution.²¹ It is related to the systemic risk measure of Acharya et al. (2010), which is a function of the marginal expected shortfall. Our measure is also related to the one adopted by Huang et al. (2009) and Chen et al. (2014); however, in their respective studies, the conditional expectation threshold

²⁰We take the median since it is less influenced by extreme values. The average would produce a similar pattern, however the series would be more volatile.

²¹This systemic risk measure is analogous to the concept of expected shortfall or conditional tail expectation.

is determined by a fraction of the total liabilities. Moreover, their prices of insurance against distressed losses are computed under the risk-neutral measure. In this study, we use the physical probabilities, as we focus on real-life expected losses. Similarly to Huang et al. (2009) and Chen et al. (2014), our measure is forward-looking as it is based on CDS data and does not require a large sample of firms.

We further divide our systemic risk measure into two components: the contribution of insurance and banking firms, respectively. These components correspond to the notion of marginal expected shortfall and could be described as the subsector's losses when the whole financial service sector is doing poorly.

To this end, we construct a theoretical debt portfolio that includes the total liabilities of each financial firm. The value of the total liabilities (i.e. LTQ) is extracted from the WRDS Compustat database; it is available for each quarter, in millions. Therefore, we use linear interpolation to obtain the total liabilities value for each week. The sum of each firm's liabilities is on average around about $\$ 1.9 \times 10^7$ millions.

As the framework is rather complicated, we rely on a Monte Carlo procedure to calculate the measures of systemic risk (SR). Appendix B provides the steps to compute the systemic risk measure along with the systemic risk contributions for each subsector which represent the subsector's respective expected losses given that the whole sector's losses are higher than the 99th percentile. Intuitively, it informs us about each subsector's systemic risk importance.

The relative contributions RSR are scaled versions of the nominal price measures. Practically, we simply divide the contributions by the sum of the total liabilities for each respective subsector. This allows us to compare the relative systemic risk contributions of each subsector readily as they share the same scale.

6.1 Systemic risk measures

Before commenting on each subsector's systemic risk contributions, we assess the importance of the loss and correlation assumptions made in the framework of Section 2. To do so, the systemic risk measure SR is computed using different modelling assumptions such as independence between firms' leverage ratios and constant recovery rates.²²

For each modelling assumption stated above, Table 4 exhibits the average systemic risk contribution across different eras. Before the crisis, the expected loss, given that the 99% VaR has been reached, is estimated at \$ 23.846 billion which corresponds to 0.9% of the total liabilities across the 35 firms. During the crisis, the conditional expected loss rose to \$ 133.959 billion of dollars, or 3.9% of the total liabilities.

During the pre-crisis period, using an endogenous recovery rate increases the measures by 6% on average.²³ Using the regime-dependent correlations have only minor impacts on the systemic risk contributions during this period: when the sector is healthy as a whole, correlation should not have large repercussions on loss distributions as defaults rarely occur.

During the crisis era, the regime-dependent correlations and the endogenous recovery rate both have a major impact on the systemic risk measure: on average, they increase the systemic risk contributions by factors of 14% and 11%, respectively. The dependence assumption has important consequences on the insurance subsector, increasing the risk contributions by 23% on average. For the same subsector, the endogenous recovery assumption increases the measures by 3%. For the banking subsector, endogenous recovery has a major impact on RSR with an average rise of 18%. Regime-dependent correlation increases the measure by a factor of 6% on average.

During the post-crisis period, the correlation assumption has the most significant effect on the insurance subsector's measures, with increases of 7% on average. For the banking subsector, the endogenous recovery assumption is the most significant one: the contributions increase by a factor of 9% on average.

In summary, it is now clear that linkage and loss are essential in explaining the rise of systemic risk during the last financial crisis. These two financial crises' "L"s have important ramifications on the measures for

²²In practice, we use the average recovery rate instead of the endogenous recovery rate of Equation (6), which varies with the leverage ratio. It removes the negative correlation between default probabilities and recovery rates.

²³This is found by taking $\frac{1}{4} (0.902/0.842 - 1 + 0.902/0.843 - 1 + 0.906/0.862 - 1 + 0.905/0.862 - 1) = 0.0605$.

Table 4: Average systemic risk measures on three different periods (i.e. pre-crisis, crisis and post-crisis) using different modelling assumptions.

Panel A: Insurance subsector						
	Pre-crisis		Crisis		Post-crisis	
	Nominal	Unit (%)	Nominal	Unit (%)	Nominal	Unit (%)
Regime correlation, endogenous recovery	23,846.2	0.902	113,959.0	3.976	64,550.8	2.301
Regime correlation, exogenous recovery	22,256.4	0.842	107,442.7	3.737	63,126.4	2.250
Independence, endogenous recovery	23,849.9	0.902	91,074.6	3.150	59,771.0	2.126
Independence, exogenous recovery	22,273.8	0.843	90,886.8	3.137	59,308.5	2.111
Panel B: Banking subsector						
	Pre-crisis		Crisis		Post-crisis	
	Nominal	Unit (%)	Nominal	Unit (%)	Nominal	Unit (%)
Regime correlation, endogenous recovery	101,571.4	0.906	782,154.6	6.166	961,985.4	9.789
Regime correlation, exogenous recovery	96,387.0	0.862	659,127.7	5.188	880,730.0	8.955
Independence, endogenous recovery	101,468.7	0.905	735,895.8	5.790	952,787.0	9.694
Independence, exogenous recovery	96,373.3	0.862	631,118.2	4.964	875,675.5	8.903

[1] The theoretical debt portfolio that includes the total liabilities of each financial. The value of the total liabilities (i.e. LTQ) is extracted from the WRDS Compustat database.

[2] The systemic risk measures are computed using Monte Carlo methods and 5×10^5 paths over a span of three months.

[3] Each systemic risk measure is computed for four different scenarios: regime-dependent correlation with endogenous recovery rates (full model), regime-dependent correlation with endogenous recovery rates, independence assumption with endogenous recovery rates, and independence assumption with exogenous recovery rates.

[4] Systemic risk measures in nominal units are given in millions.

both subsectors. For instance, independence completely underestimates the tail risk in general, and especially in periods of turmoil. Thus, regime-dependent correlation is important in explaining systemic risk during periods of crisis.

Now focusing on the contributions given by the model described in Section 2, we display the time series of nominal and unit price contributions in Figure 9. The top panel represents the systemic risk contributions in nominal terms. The banking subsector contribution always lies above the insurance subsector's time series: not surprisingly, the banking subsector's total liabilities are larger than those of the insurance subsector, implying larger marginal expected shortfalls.

The unit price contributions are given in the bottom panel of Figure 9. The two subsectors' contributions are similar during the pre-crisis era. However, at the beginning of the crisis, the banking contribution rises quickly, capturing the increase in systemic risk for this subsector. Halfway through the crisis, the insurance contribution jumps from 1% to almost 20%: this rise is consistent with AIG's near-default and the increased credit risk in Lincoln National, XL and Genworth. In the post-crisis era, the banking systemic risk remains high and increases from 9% to 15% during the European debt crisis. The insurance subsector's contribution slowly decreases to reach pre-crisis levels at the end of the sample.

The sample correlation between the relative systemic risk contribution of insurers and banks, RSR_t^{Ins} and RSR_t^{Bnk} , respectively, is about 30% for the 2005–2012 period, which is rather low. When we consider only the crisis era, this sample correlation escalates to 69%, implying large comovements in both subsectors' contributions. For the remainder of the paper, we focus on the unit price contributions.

6.2 Granger causality tests

At this point, it would be interesting to look at causality: as in Chen et al. (2014), we would like to test whether a subsector's contribution could be used to forecast the other's systemic risk. As a starting point, linear Granger (1969) causality tests are employed. The latter involves F -tests to determine whether lagged data on a variable Y provides any statistically significant information on another variable X in the presence

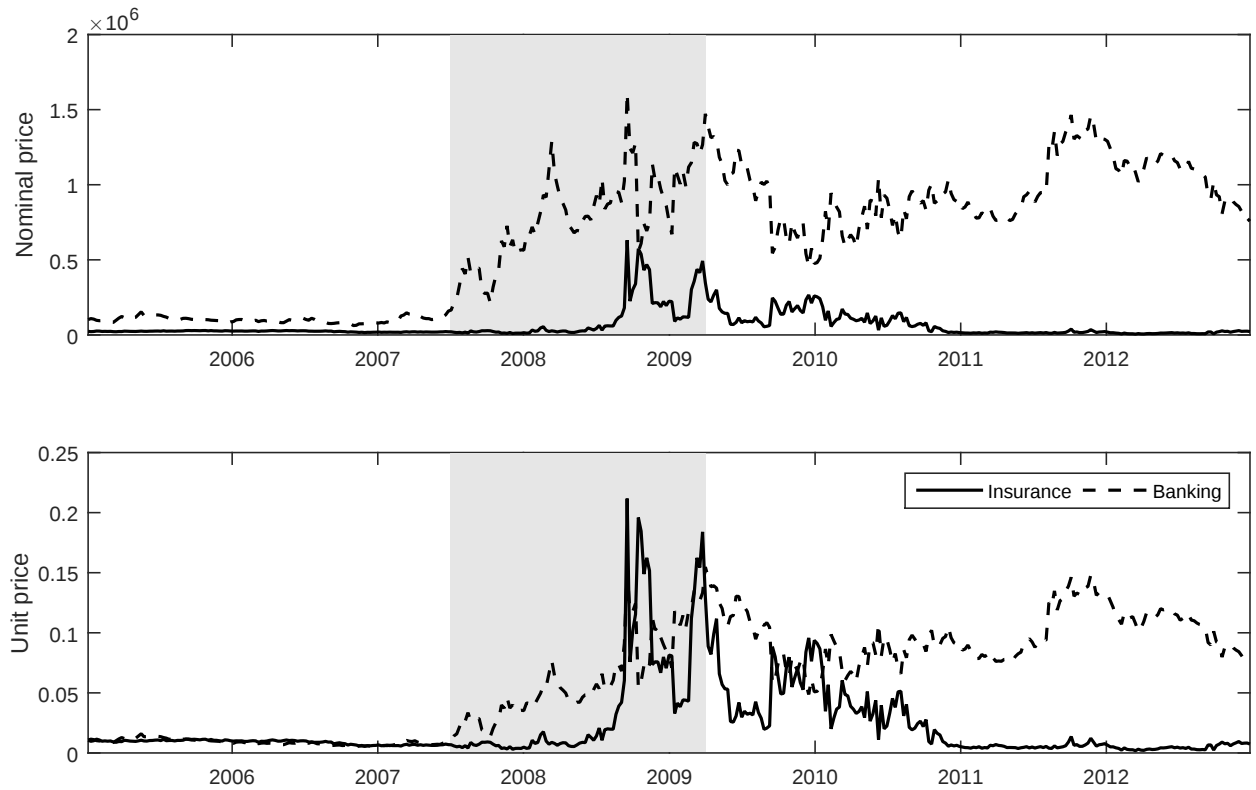


Figure 9: Time series of the systemic risk measure contribution (i.e. SR_t^{Ins} and SR_t^{Bnk}) and the relative systemic risk measure contribution (i.e. RSR_t^{Ins} and RSR_t^{Bnk}) using the full model.

The systemic risk measures are computed using Monte Carlo methods and 5×10^5 paths over a span of three months. The theoretical debt portfolio that includes the total liabilities of each financial.

of lagged values of X . In this spirit, the null hypothesis of this statistical test should read: Y does not Granger-cause X .

Even though this test is very popular in the empirical literature, the linear Granger causality test does not capture nonlinear and higher-order causal relationships. To grasp these nonlinear effects, we also use nonlinear Granger causality tests. A general version of the nonlinear causality tests was first developed by Baek and Brock (1992) and then modified by Hiemstra and Jones (1994). However, Diks and Panchenko (2006) show that the Hiemstra and Jones (1994)'s statistical test could overreject the null hypothesis given that the rejection probabilities may tend to one as the sample size increases. They also propose a new nonparametric test for nonlinear Granger causality that avoids the over-rejection issue. Therefore, in this paper, we use Diks and Panchenko (2006)'s (hereinafter DP) statistic to test causality in the nonlinear case.

Granger causality tests require stationary time series; however, the subsector systemic risk measures are both non-stationary. By visual inspection of Figure 9, it is explicit that these series are not stationary.²⁴ Therefore, we difference both series. ADF tests are done on the differenced time series and the null hypothesis is rejected for both series this time.²⁵

Also, as noted in Hiemstra and Jones (1994), heteroskedasticity could lead to a substantial bias. By visually inspecting the autocorrelation functions of squared differenced contributions (top panels of Figure 10), we conclude that there is conditional heteroskedasticity in both time series. We follow Chen et al. (2014) and deal with it by using a generalized autoregressive conditional heteroskedasticity (GARCH) model. For insurance and banking subsectors' contributions, we estimate a GARCH(1,1) model and extract the Gaussian

²⁴Indeed, augmented Dickey-Fuller (ADF) tests fail to reject the null hypothesis for both systemic risk contributions.

²⁵For the insurance subsector: ADF-statistic of -26.45 and a p -value below 0.1%. For the banking subsector: ADF-statistic of -24.24 and a p -value below 0.1%.

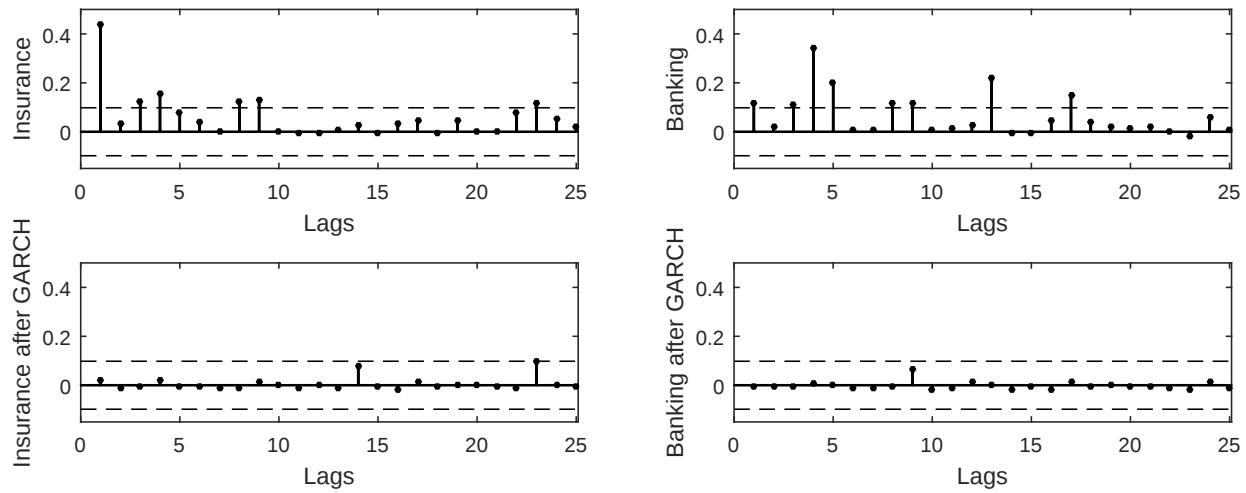


Figure 10: Sample autocorrelation functions for squared differenced systemic risk contributions and squared GARCH noise terms.

The systemic risk measure contributions are computed using Monte Carlo methods and 5×10^5 paths over a span of three months. The theoretical debt portfolio that includes the total liabilities of each financial. The GARCH noise terms are computed by fitting a GARCH(1,1) model to the differenced systemic risk contributions and by extracting the Gaussian noise terms.

noise processes. To assess if there is any residual heteroskedasticity, we plot the autocorrelation functions of the squared noise terms (bottom panels of Figure 10). It seems that the GARCH(1,1) model sufficiently accounts for the conditional heteroskedasticity in the original time series.

Using the noise process for both subsectors' contributions (i.e. post-GARCH filtering), we run the linear and nonlinear Granger causality tests. Table 5 shows the various results for both causality tests and for both subsectors.²⁶

In terms of linear Granger tests, the systemic risk of banking firms causes the systemic risk of insurance companies. For the opposite relationship, we cannot reject the null hypothesis: we cannot conclude that the systemic risk of insurers Granger-causes the systemic risk of banks.

For the nonlinear case, the banking subsector's systemic risk only Granger-causes the insurance subsector's systemic risk when the lag length is equal to one (at a confidence level of 95%). However, the insurer's systemic risk does not Granger-cause the bank's systemic risk for any lag length.

These results are in line with Chen et al. (2014): there is a unidirectional causal effect from banks to insurers when accounting for heteroskedasticity while the opposite relationship (from insurers to banks) is not statistically significant. Therefore, even if our methodology differs and our data extends over the aftermath of the crisis, our results suggest that the direction of the causal relationship is robust. The systemic risk results are also consistent with Billio et al. (2012) who find that banks tend to have a much more important role in the transmission of shocks.

7 Concluding remarks

Unlike conventional empirical studies of credit risk, this paper focuses on the financial services sector. To adequately model three out of the four financial crises "L"s, a Markov-switching extension of the hybrid credit risk model of Boudreault et al. (2014) is proposed. The latter allows for firm-specific statistical regimes that accommodate for changes in the leverage uncertainty, an endogenous stochastic recovery rate that is negatively related to the default probabilities, and pairwise correlations of leverages' co-movements.

²⁶Appendix C provides results for linear and nonlinear Granger tests based on differenced time series (i.e. before GARCH filtering).

Table 5: Linear and nonlinear Granger causality tests after GARCH filtering.

Panel A: Linear Granger causality.							
X = Insurance, Y = Banking				X = Banking, Y = Insurance			
L_X	L_Y	F -statistics	p -value	L_X	L_Y	F -statistics	p -value
1	1	4.991	0.026	1	1	1.464	0.227
Panel B: Nonlinear Granger causality using Diks and Panchenko (2006).							
X = Insurance, Y = Banking				X = Banking, Y = Insurance			
L_X	L_Y	DP-statistics	p -value	L_X	L_Y	DP-statistics	p -value
1	1	1.745	0.040	1	1	0.789	0.215
2	2	1.418	0.078	2	2	1.382	0.084
3	3	0.892	0.186	3	3	0.239	0.406
4	4	0.826	0.204	4	4	0.649	0.258
5	5	0.866	0.193	5	5	0.106	0.458
6	6	0.783	0.217	6	6	0.408	0.342
7	7	0.828	0.204	7	7	0.638	0.262
8	8	0.636	0.262	8	8	0.545	0.293

- [1] This table provides the various statistics and p -values associated with Granger causality tests after GARCH filtering. Broadly speaking, the null hypothesis is $H_0 : Y$ does not Granger-cause X . Therefore, the leftmost columns show whether the systemic risk of banks does Granger-cause systemic risk of insurers. Moreover, the rightmost columns show whether the systemic risk of insurers does Granger-cause systemic risk of banks.
- [2] L_X and L_Y are the number of lags of X and Y , respectively. For the linear case, they are determined using the Bayesian information criterion.
- [3] Values in bold denote a significance level of 5%.
- [4] We use a lead length of 1 and a bandwidth of 0.5 in Diks and Panchenko (2006).
- [5] The GARCH noise terms are computed by fitting a GARCH(1,1) model to the differenced systemic risk contributions and by extracting the Gaussian noise terms.

The firm-by-firm estimation of the model is based on the entire term structure of single-name CDS premiums of 35 major financial institutions and uses a two-stage filtering technique.

The model provides a framework that reacts quickly to new information and is well adapted to measure firm-specific credit risk, even during financial turmoil. We find that the banking subsector's default probabilities are higher during the first half of the crisis era. Halfway through the crisis period, the insurance subsector's average PDs are tremendously affected.

Our results indicate an increase in correlation during the high-volatility regime in comparison with the stable regime for 33 out of the 35 firms within the portfolio. It suggests the existence of a strong linkage among many financial institutions under study during the last crisis.

Finally, the empirical study presented in this paper finds supportive evidence of increased systemic risk within the financial services sector during the last global crisis. There is a unidirectional causal effect from banks to insurers when accounting for heteroskedasticity. However, the opposite relationship (from insurers to banks) is not statistically significant.

Possible extensions of the framework would account for the fourth financial crises' "L": liquidity. This would obviously require the incorporation of an efficient liquidity proxy that captures this dimension. The inclusion of this aspect is not trivial. We leave this question for further research.

Appendices

Appendix A Endogenous correlation coefficients

To obtain endogenous correlation estimates, correlation coefficients are introduced into the covariance matrix of the augmented state vector on which the unscented transformation is performed. As a starting point, one can write the second order moment of the augmented state vector as

$$\mathbf{P}_{t|t}^a = \begin{bmatrix} \mathbf{P}_{t|t} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_{\mathbf{s}_t} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{R} \end{bmatrix}_{2(D+2) \times 2(D+2)}$$

where $[\mathbf{P}_{t|t}]_{2 \times 2}$ is the covariance matrix of predicted state variables $(\hat{x}_{t|t}^{(i)}, \hat{x}_{t|t}^{(j)})$ updated at each time step, $[\boldsymbol{\Sigma}_{\mathbf{s}_t}]_{2 \times 2}$ is the covariance matrix of leverage noise terms associated with regimes $\mathbf{s}_t = (s_t^{(i)}, s_t^{(j)})$, and $[\mathbf{R}]_{2D \times 2D}$ is the trading noise variance matrix. Furthermore, dimension D refers to the number of CDS maturities available for each firm. More precisely, covariance and variance matrices can be expressed as

$$\boldsymbol{\Sigma}_{\mathbf{s}_t} = \begin{bmatrix} (\sigma_{\mathbf{s}_t}^{(i)})^2 & \sigma_{\mathbf{s}_t}^{(i)} \sigma_{\mathbf{s}_t}^{(j)} \rho_{\mathbf{s}_t}^{(i,j)} \\ \sigma_{\mathbf{s}_t}^{(i)} \sigma_{\mathbf{s}_t}^{(j)} \rho_{\mathbf{s}_t}^{(i,j)} & (\sigma_{\mathbf{s}_t}^{(j)})^2 \end{bmatrix} \times \Delta t \text{ and } \mathbf{R} = \text{diag}(\delta^2).$$

Note that $\text{diag}(\delta^2)$ is the operator that creates a square matrix with diagonal elements corresponding to δ^2 , and $\delta = [\delta^{(i,1)}, \delta^{(i,2)}, \delta^{(i,3)}, \delta^{(i,5)}, \delta^{(i,7)}, \delta^{(i,10)}, \delta^{(j,1)}, \delta^{(j,2)}, \delta^{(j,3)}, \delta^{(j,5)}, \delta^{(j,7)}, \delta^{(j,10)}]$ is the vector of the noise terms' standard deviation. By maximizing the joint bivariate log-likelihood function, one obtains the correlation coefficient estimates.

According to Hamilton (1994) and considering M parallel UKF in the bivariate framework, the (quasi-) log-likelihood function based on observations $\mathbf{y}_t = (\mathbf{y}_t^{(i)}, \mathbf{y}_t^{(j)})$ up to time step T for all possible paths M is computed by

$$\sum_{t=1}^T \sum_{l=1}^M \log(f(\mathbf{y}_t | Y_{t-1}; \phi_2))$$

where $\phi_2 = \{\rho_{(1,1)}^{(i,j)}, \rho_{(1,2)}^{(i,j)}, \rho_{(2,1)}^{(i,j)}, \rho_{(2,2)}^{(i,j)}\}$, and the conditional likelihood $f(\mathbf{y}_t | Y_{t-1}; \phi_2)$ given $Y_{t-1} = \{\mathbf{y}_1^{(i)}, \dots, \mathbf{y}_{t-1}^{(i)}, \mathbf{y}_1^{(j)}, \dots, \mathbf{y}_{t-1}^{(j)}\}$ is the probability density function of a $2D$ -variate Gaussian distribution valued at $(\mathbf{y}_t^{(i)}, \mathbf{y}_t^{(j)})$ with mean and covariance obtained from the filtering procedure. More specifically, the mean $(\hat{\mathbf{y}}_{t|t-1}^{(i)}, \hat{\mathbf{y}}_{t|t-1}^{(j)})$ is a $(1 \times 2D)$ vector obtained from $\mathbb{E}[(\mathbf{y}_t^{(i)}, \mathbf{y}_t^{(j)}) | Y_{t-1}]$, and the covariance matrix of dimension $(2D \times 2D)$ is $\mathbf{P}_{\mathbf{y}\mathbf{y}} = \text{Cov}[(\mathbf{y}_t^{(i)}, \mathbf{y}_t^{(j)}), (\mathbf{y}_t^{(i)}, \mathbf{y}_t^{(j)}) | Y_{t-1}]$.²⁷ By using Bayes' rule, one can express the conditional likelihood function as

$$f(\mathbf{y}_t | Y_{t-1}; \phi_2) = \frac{\sum_{\mathbf{s}_t} f(\mathbf{y}_t, \mathbf{s}_t, Y_{t-1}; \phi_2)}{f(Y_{t-1}; \phi_2)} = \sum_{\mathbf{s}_t} f(\mathbf{y}_t | \mathbf{s}_t, Y_{t-1}; \phi_2) \times f(\mathbf{s}_t | Y_{t-1}; \phi_2).$$

The conditional likelihood of $\mathbf{y}_t = (\mathbf{y}_t^{(i)}, \mathbf{y}_t^{(j)})$ is computed analytically using the $2D$ -variate Gaussian density function. From the Markov property, the likelihood function given $\mathbf{y}_{t-1} = (\mathbf{y}_{t-1}^{(i)}, \mathbf{y}_{t-1}^{(j)})$ and the actual regimes $\mathbf{s}_t = (s_t^{(i)}, s_t^{(j)})$ of firms i and j can be expressed as

$$f(\mathbf{y}_t | \mathbf{s}_t, Y_{t-1}; \phi_2) = f(\mathbf{y}_t | \mathbf{s}_t, \mathbf{y}_{t-1}; \phi_2) = \frac{1}{(2\pi)^D |\mathbf{P}_{\mathbf{y}\mathbf{y}}|^{1/2}} \exp\left(-\frac{1}{2} e_{\mathbf{s}_t}^\top \mathbf{P}_{\mathbf{y}\mathbf{y}}^{-1} e_{\mathbf{s}_t}\right)$$

where $e_{\mathbf{s}_t}$ is the error between observations and their forecast values. Second, the conditional likelihood of $\mathbf{s}_t = (s_t^{(i)}, s_t^{(j)})$ given Y_{t-1} is obtained recursively. Let $\eta_t^\top = f(\mathbf{y}_t | \mathbf{s}_t, Y_{t-1}; \phi_2)$ and $\xi_{t|t-1} = f(\mathbf{s}_t | Y_{t-1}; \phi_2)$

²⁷The two moments are computed as a by-product of the UKF methodology.

be two vectors of size 4×1 . Then, one can use the following recursion equations

$$\xi_{t+1|t} = \mathbf{P}^{(i,j)\top} \xi_{t|t} \quad \text{and} \quad \xi_{t|t} = \frac{\eta_t(\times) \xi_{t|t-1}}{\eta_t^\perp \xi_{t|t-1}}$$

where $(\times)$ refers to the element-by-element multiplication and $\mathbf{P}^{(i,j)}$ is the following transition matrix

$$\mathbf{P}^{(i,j)} = \begin{bmatrix} p_{11}^{(i)} p_{11}^{(j)} & p_{11}^{(i)} p_{12}^{(j)} & p_{12}^{(i)} p_{11}^{(j)} & p_{12}^{(i)} p_{12}^{(j)} \\ p_{11}^{(i)} p_{21}^{(j)} & p_{11}^{(i)} p_{22}^{(j)} & p_{12}^{(i)} p_{21}^{(j)} & p_{12}^{(i)} p_{22}^{(j)} \\ p_{21}^{(i)} p_{11}^{(j)} & p_{21}^{(i)} p_{12}^{(j)} & p_{22}^{(i)} p_{11}^{(j)} & p_{22}^{(i)} p_{12}^{(j)} \\ p_{21}^{(i)} p_{21}^{(j)} & p_{21}^{(i)} p_{22}^{(j)} & p_{22}^{(i)} p_{21}^{(j)} & p_{22}^{(i)} p_{22}^{(j)} \end{bmatrix}.$$

An estimate of ϕ_2 is obtained by maximizing the log-likelihood function:

$$\hat{\phi}_2 = \operatorname{argmax} \left\{ \sum_{t=1}^T \sum_{l=1}^M \sum_{\mathbf{s}_t} \ln(\xi_{t|t-1}) - D \ln(2\pi) - \frac{1}{2} \ln |\mathbf{P}_{\mathbf{y}\mathbf{y}}| - \frac{1}{2} \mathbf{e}_{\mathbf{s}_t}^\top \mathbf{P}_{\mathbf{y}\mathbf{y}}^{-1} \mathbf{e}_{\mathbf{s}_t} \right\}.$$

Appendix B Calculation of systemic risk measures

Algorithm 1 (Calculation of systemic risk measures)

1. Generate 500,000 log-leverage paths of three months (i.e. 13 weeks), along with default indicators and losses given default.

(a) For each firm i , generate the time $t + u$ log-leverage such that

$$\log(X_{t+u}^{(i)}) = \log(X_{t+u-1}^{(i)}) + \left(\mu^{(i)} - \frac{1}{2} \left(\sigma_{s_{t+u}}^{(i)} \right)^2 \right) \Delta t + \sum_{j=1}^N R_{s_{t+u}}^{(i,j)} \sqrt{\Delta t} \varepsilon_{t+u}^{(j)}$$

where $R_{s_{t+u}}^{(i,j)}$ is the (i,j) -th entry of the (lower triangular) Cholesky decomposition of the regime-dependent covariance matrix and $\varepsilon_{t+u}^{(j)}$ are standardized Gaussian random variables.²⁸

- (b) Determine if the remaining firms default. This step is performed using the model's PD over the next week:

$$PD_{t+u-1,t+u}^{(i)} = 1 - \exp \left[-\Delta t \left(\beta^{(i)} + \left(\frac{X_{t+u-1}^{(i)}}{\theta^{(i)}} \right)^{\alpha^{(i)}} \right) \right].$$

Firm i defaults if $U_{t+u}^{(i)} \leq PD_{t+u-1,t+u}^{(i)}$ where $U_{t+u}^{(i)}$ is a uniformly distributed random variable $U_{t+u}^{(i)}$ on $[0, 1]$.

- (c) For each firm i , compute the loss given default

$$LGD_{t+u}^{(i)} = \begin{cases} TL_{t+u}^{(i)} \left(1 - \min \left[\frac{1}{X_{t+u}^{(i)}} (1 - \kappa^{(i)}) ; 1 \right] \right) & \text{if the firm defaults} \\ 0 & \text{otherwise} \end{cases}$$

where $TL_{t+u}^{(i)}$ is the i -th firm total liabilities at time $t + u$. The i -th firm is removed from the set of active companies if it defaults.

2. Aggregate each firm's losses and compute the total losses across the firms:

$$L_{t,t+13}^{(i)} = \sum_{u=1}^{13} LGD_{t+u}^{(i)} \quad \text{and} \quad L_{t,t+13} = \sum_{i=1}^N L_{t,t+13}^{(i)}.$$

²⁸Since the correlation coefficients are estimated in a pairwise manner, it is possible that the full correlation matrix is not positive-definite. Following the literature, we find the closest correlation matrices in the Frobenius norm. In this paper, Qi and Sun (2006)'s method is applied. The nearest symmetric correlation matrix is the closest to the estimated correlation matrix in the sense of the Frobenius norm. Qi and Sun (2006)'s method is highly efficient and converges readily.

3. Compute the systemic risk measure (SR) for the financial service sector as the sample average across the 500,000 log-leverage paths of

$$L_{t,t+13} \mathbb{I}(L_{t,t+13} > VaR_{0.99}(L_{t,t+13})), \quad (B1)$$

where $VaR_{0.99}(L_t)$ represents the 99th percentile of the total losses distribution and $\mathbb{I}(\cdot)$ the indicator function.

4. Finally, calculate the systemic risk contribution (so-called nominal price, in millions) for each subsector (i.e. the marginal expected shortfall). This is the sample average across the 500,000 log-leverage paths of

$$\left(\sum_{i \in SS} L_{t,t+13}^{(i)} \right) \mathbb{I}(L_{t,t+13} > VaR_{0.99}(L_{t,t+13})), \quad (B2)$$

where $SS \in \{\text{Ins}, \text{Bnk}\}$. Also, compute the relative systemic risk contribution RSR_t^{SS} (so-called unit price, as a percentage) for each subsector by dividing each systemic risk contribution by the subsector's total liabilities.

Appendix C

C.1 Parameters: First stage

Table C1 exhibits the firm-specific parameters for each of the 35 companies considered in this study.

C.2 Firm-specific regimes

Figures C1 and C2 show the filtered firm-specific regimes along with 1-, 5-, and 10-year CDS log-premiums.

C.3 Firm-specific probabilities of default

Figures C3 and C4 exhibit the filtered 5-year default probabilities along with those computed using the default count approach.

C.4 Parameters: Second stage

Table C2 exhibits the descriptive statistics of correlation estimates.

Tables C3 to C6 show the correlation estimates for each of the 35 companies considered in this study and for each regime combination (i.e. (1,1), (2,2), (1,2), and (2,1)).

C.5 Systemic risk measures: Additional results

C.5.1 Linear Granger causality tests

First, let us focus on whether the systemic risk of banking firms Granger-causes the systemic risk of insurance companies. The results of this statistical test is given in Panel A of Table C7. As usual, we search for the optimal number of lags based on the Bayesian information criterion (BIC).²⁹ The statistical test reports whether the coefficients of the lagged RSR^{Bnk} are jointly significantly different from zero. The F -statistic has a value of 6.199 and the null hypothesis is rejected at a level of 1%, meaning that the banking subsector systemic risk Granger-causes the insurance subsector systemic risk.

²⁹For the restricted model (i.e. the one using only insurance subsector contributions' lagged values), we find one lag for insurers. Then, using the unrestricted model (i.e. the one that includes banking subsector contributions' in lagged values), we detect five lags for banks.

Table C1: First-stage parameter estimates.

Firm	$\mu^Q(\%)$	$\mu^P(\%)$	σ_1	σ_2	$p_{11}^Q(\%)$	$p_{11}^P(\%)$	$p_{22}^Q(\%)$	$p_{22}^P(\%)$	κ	α	θ	$\beta(\%)$	$\delta^{(1)}$	$\delta^{(2)}$	$\delta^{(3)}$	$\delta^{(5)}$	$\delta^{(7)}$	$\delta^{(10)}$
ACE	-0.039	-0.129	0.069	0.360	99.393	97.208	92.358	95.293	0.448	11.373	1.362	0.156	0.197	0.137	0.088	0.044	0.013	0.037
ALL	0.027	-0.184	0.068	0.358	99.538	98.962	95.562	94.347	0.577	8.599	1.302	0.162	0.328	0.215	0.139	0.040	0.008	0.037
AXP	-0.079	-0.072	0.080	0.359	99.712	96.558	96.206	99.394	0.646	9.159	1.288	0.062	0.228	0.119	0.070	0.070	0.071	0.111
AIG	0.041	-0.242	0.081	0.359	99.640	98.531	96.466	96.740	0.632	14.122	1.413	0.096	0.318	0.144	0.070	0.044	0.043	0.080
AOC	-0.005	-0.035	0.098	0.358	99.665	97.985	94.153	97.675	0.514	8.573	1.389	0.001	0.327	0.131	0.065	0.040	0.056	0.066
BSC	-0.018	-0.040	0.055	0.319	99.822	98.896	94.701	98.536	0.475	15.341	1.288	0.054	0.187	0.131	0.079	0.050	0.017	0.042
BRK	-0.015	-0.038	0.060	0.360	99.607	96.676	89.098	95.932	0.643	10.852	1.346	0.000	0.237	0.120	0.078	0.054	0.041	0.066
BACORP	0.014	-0.089	0.070	0.359	99.652	90.481	93.835	96.902	0.644	8.516	1.374	0.006	0.343	0.159	0.098	0.052	0.021	0.034
COF	-0.163	0.014	0.087	0.359	99.688	96.706	95.905	99.729	0.443	9.471	1.442	0.130	0.233	0.161	0.112	0.059	0.013	0.042
SCH	-0.045	-0.017	0.075	0.360	99.633	98.588	93.686	92.114	0.531	7.341	1.276	0.001	0.243	0.158	0.086	0.059	0.059	0.099
CB	-0.014	-0.015	0.070	0.358	99.458	98.520	94.928	99.081	0.585	10.071	1.372	0.114	0.260	0.124	0.083	0.059	0.037	0.048
C	-0.022	-0.221	0.062	0.358	99.436	95.178	91.108	93.940	0.535	8.973	1.448	0.000	0.348	0.179	0.101	0.045	0.007	0.037
DB	-0.039	-0.036	0.032	0.313	98.932	98.467	96.178	99.508	0.541	16.012	1.284	1.238	0.143	0.062	0.036	0.072	0.040	0.071
FHLMC	-0.426	1.385	0.057	0.344	99.338	99.994	93.335	99.999	0.507	11.637	1.507	0.081	0.243	0.140	0.092	0.064	0.018	0.055
FNMA	0.020	0.339	0.054	0.354	99.597	99.829	96.133	99.655	0.604	9.984	1.510	0.067	0.244	0.147	0.095	0.049	0.030	0.062
GNWTH	-0.073	0.013	0.058	0.339	99.714	98.698	93.086	99.160	0.495	11.635	1.574	0.000	0.349	0.209	0.145	0.049	0.006	0.051
GS	-0.023	-0.052	0.052	0.328	99.651	97.316	92.885	89.124	0.492	11.975	1.407	0.000	0.220	0.124	0.084	0.034	0.036	0.066
HIG	0.034	-0.048	0.088	0.332	99.521	95.802	92.440	92.082	0.653	10.452	1.361	0.000	0.204	0.102	0.085	0.047	0.039	0.071
JPM	-0.011	-0.040	0.056	0.329	99.328	96.146	93.722	99.311	0.531	17.648	1.166	0.176	0.288	0.168	0.120	0.061	0.020	0.056
LEH	-0.905	-0.027	0.075	0.306	99.867	99.478	94.936	96.968	0.621	15.488	1.334	0.030	0.181	0.098	0.056	0.031	0.040	0.062
LIBMUT	-0.056	-0.136	0.078	0.341	99.473	98.350	93.730	96.753	0.643	9.022	1.254	0.011	0.182	0.103	0.067	0.035	0.028	0.055
LNC	-0.008	-0.094	0.099	0.355	99.213	98.105	93.861	98.792	0.669	8.672	1.330	0.064	0.180	0.081	0.037	0.053	0.041	0.062
LTR	0.086	-0.112	0.079	0.339	99.617	97.346	92.328	97.922	0.550	9.195	1.244	0.002	0.204	0.108	0.055	0.050	0.045	0.085
MMC	-0.096	0.007	0.088	0.339	99.678	98.353	92.761	98.077	0.580	10.602	1.231	0.022	0.227	0.105	0.080	0.009	0.044	0.078
MER	0.002	-0.015	0.063	0.349	99.764	97.033	94.582	99.548	0.570	10.477	1.396	0.000	0.329	0.179	0.113	0.052	0.010	0.042
MET	-0.045	0.071	0.082	0.360	99.372	96.715	96.298	92.308	0.649	8.716	1.198	0.228	0.275	0.158	0.086	0.032	0.018	0.038
MWD	-0.058	0.027	0.057	0.350	99.715	97.645	92.667	98.801	0.542	11.940	1.211	0.000	0.247	0.146	0.072	0.038	0.045	0.069
PRU	-0.072	0.003	0.064	0.357	99.795	98.648	95.235	91.788	0.538	10.977	1.455	0.000	0.330	0.176	0.105	0.051	0.007	0.046
SAFC	-0.051	-0.007	0.052	0.352	99.405	99.207	93.646	97.616	0.554	10.191	1.467	0.059	0.199	0.140	0.083	0.048	0.040	0.063
STI	-0.237	0.162	0.075	0.328	99.646	99.092	91.284	96.901	0.612	8.370	1.267	0.000	0.266	0.212	0.106	0.088	0.103	0.075
USB	-0.029	0.068	0.067	0.349	99.582	98.499	94.623	98.449	0.636	7.260	1.207	0.000	0.212	0.202	0.125	0.104	0.088	0.120
WM	-0.077	-0.073	0.065	0.347	99.885	96.914	95.850	98.662	0.512	13.053	1.258	0.000	0.164	0.162	0.076	0.069	0.021	0.053
WB	-0.026	-0.030	0.067	0.350	99.475	97.831	94.387	98.471	0.613	7.896	1.341	0.061	0.172	0.125	0.073	0.056	0.017	0.049
WFC	-0.043	0.030	0.094	0.360	99.640	98.151	93.384	87.055	0.457	12.428	1.375	0.264	0.248	0.120	0.085	0.046	0.065	0.102
XL	-0.147	-0.091	0.069	0.362	99.502	96.712	94.188	94.950	0.527	9.319	1.549	0.002	0.194	0.119	0.076	0.039	0.042	0.066

[1] The table shows parameters estimates obtained from CDS data from January 2005 to December 2012 by applying filtering techniques and quasi-likelihood maximization.

[2] More specifically, the following parameter are reported: the drifts μ under both measures $\mathbb{P}$ and $\mathbb{Q}$, the diffusions σ for each regime, p_{11} and p_{22} which are the probabilities to stay in low- and high-volatility regimes, respectively; the constants α , β and θ that define the intensity process, the liquidation and legal fees parameter κ , and finally the standard errors of the trading noise for tenors of 1, 2, 3, 5, 7 and 10 years.

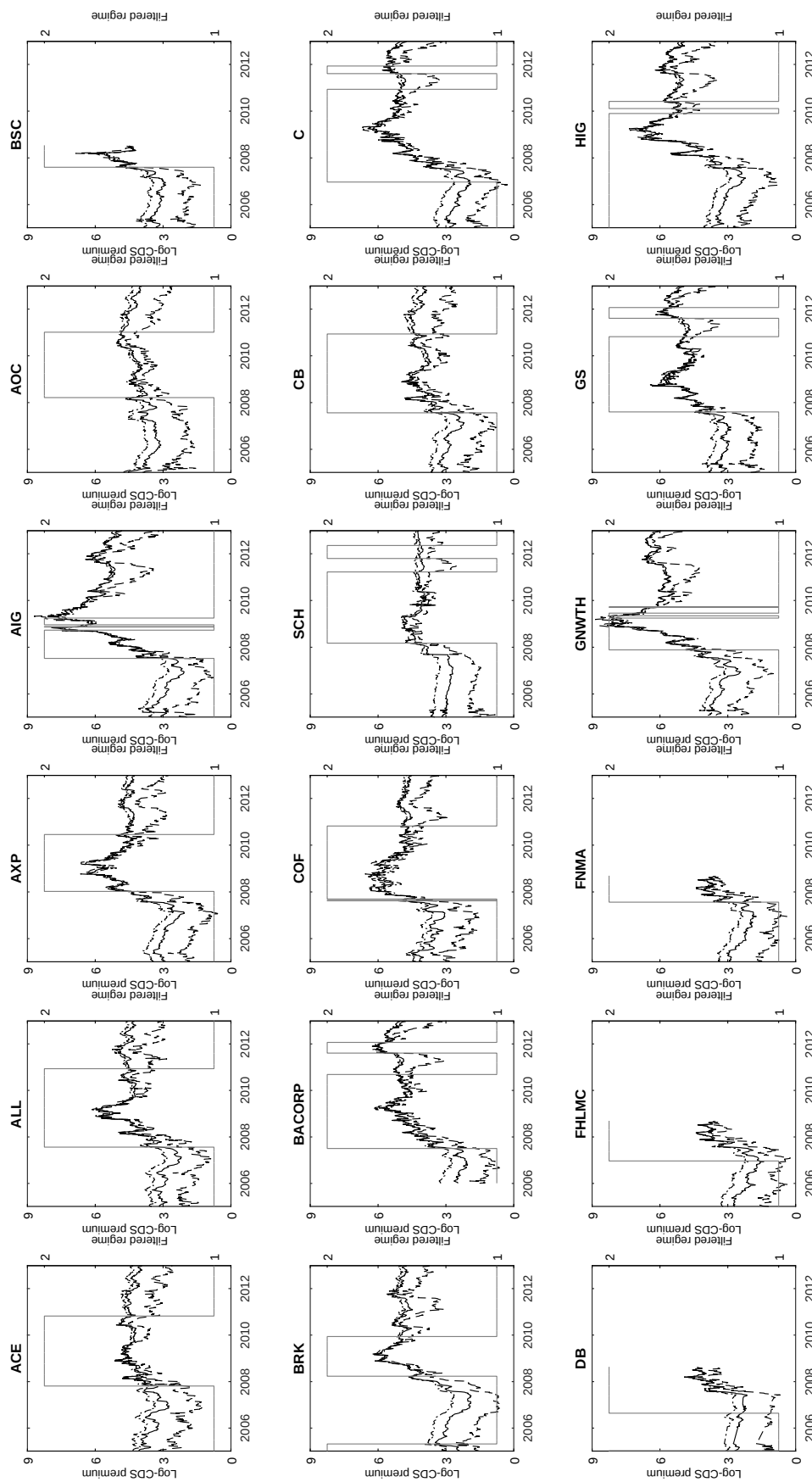


Figure C1: Filtered firm-specific regimes along with 1-, 5-, and 10-year CDS log-premiums.

This figure shows the time series of firm-specific regimes and 1-, 5-, and 10-year CDS log-premiums over the period of time 2005–2012. Filtered leverages and regimes are inferred using parameters estimated on a firm-by-firm basis.

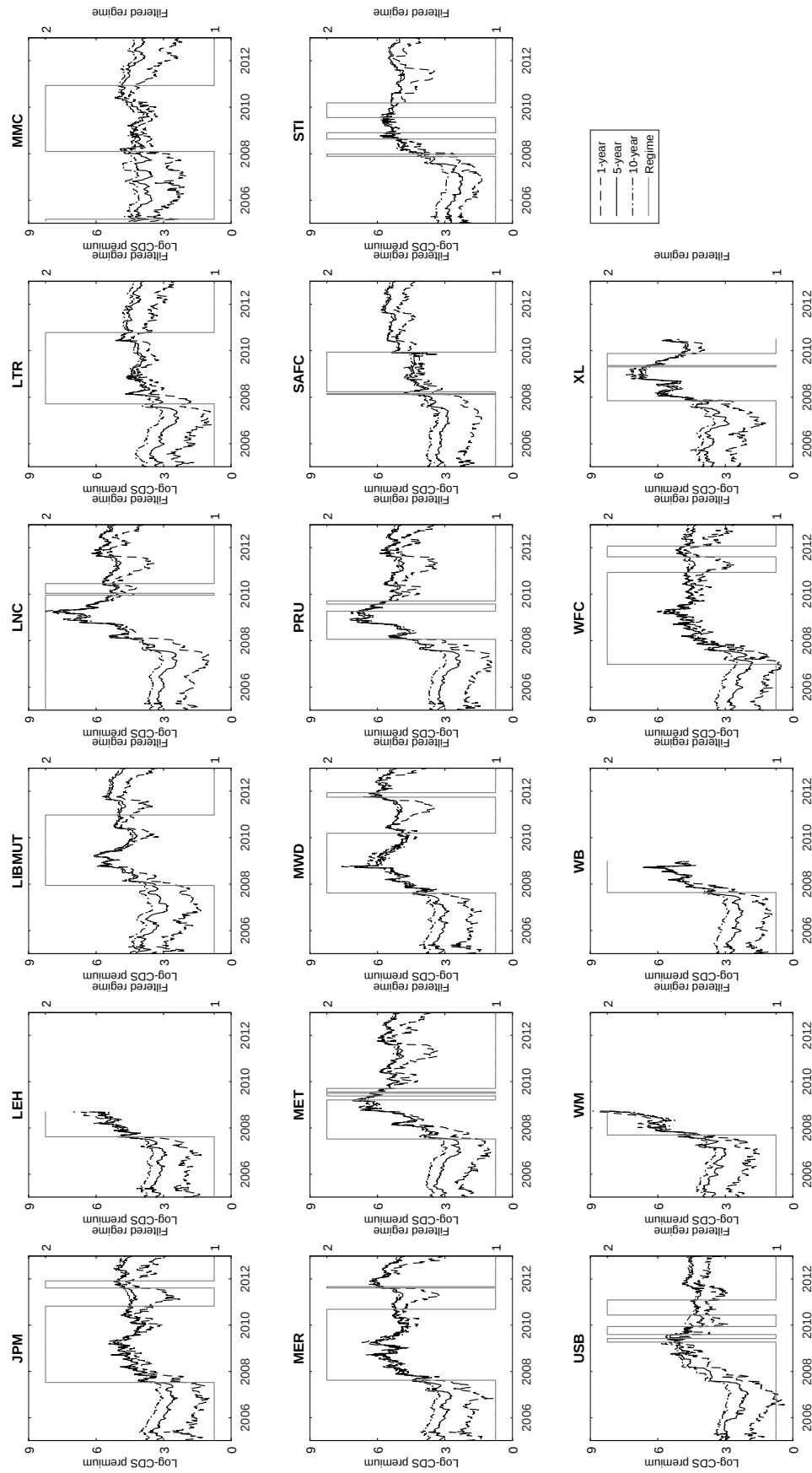


Figure C2: Filtered firm-specific regimes along with 1-, 5-, and 10-year CDS log-premiums, continued.

This figure shows the time series of firm-specific regimes and 1-, 5-, and 10-year CDS log-premiums over the period of time 2005–2012. Filtered leverages and regimes are inferred using parameters estimated on a firm-by-firm basis.

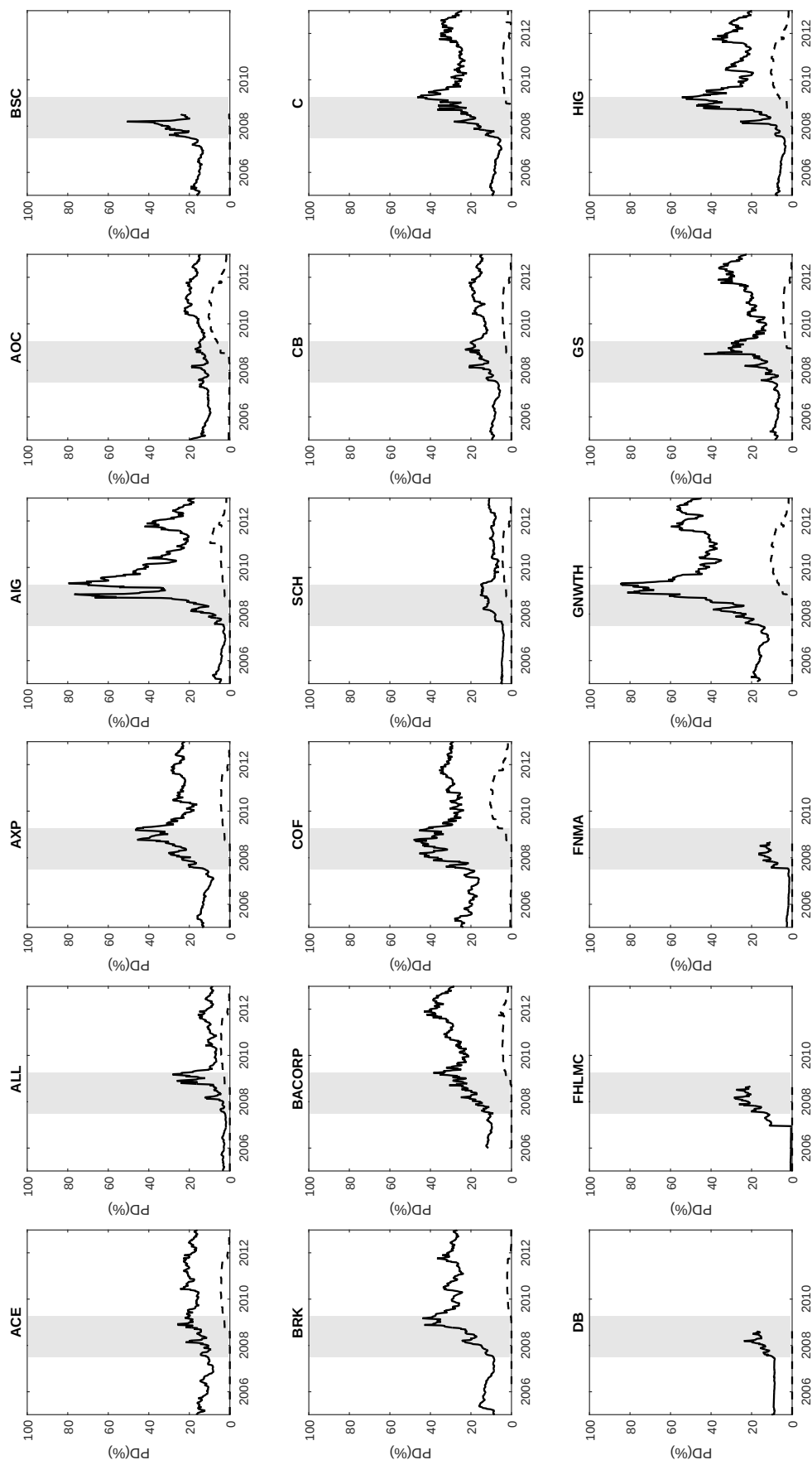


Figure C3: Filtered firm-specific probabilities of default for a 5-year time horizon along with default count approach probabilities of default.

This figure shows the time series of firm-specific 5-year probabilities of default. Two methods are used to compute the default probabilities: the credit presented in the study (solid) and a default count approach (dashed). Filtered leverages and regimes are inferred using parameters estimated on a firm-by-firm basis.

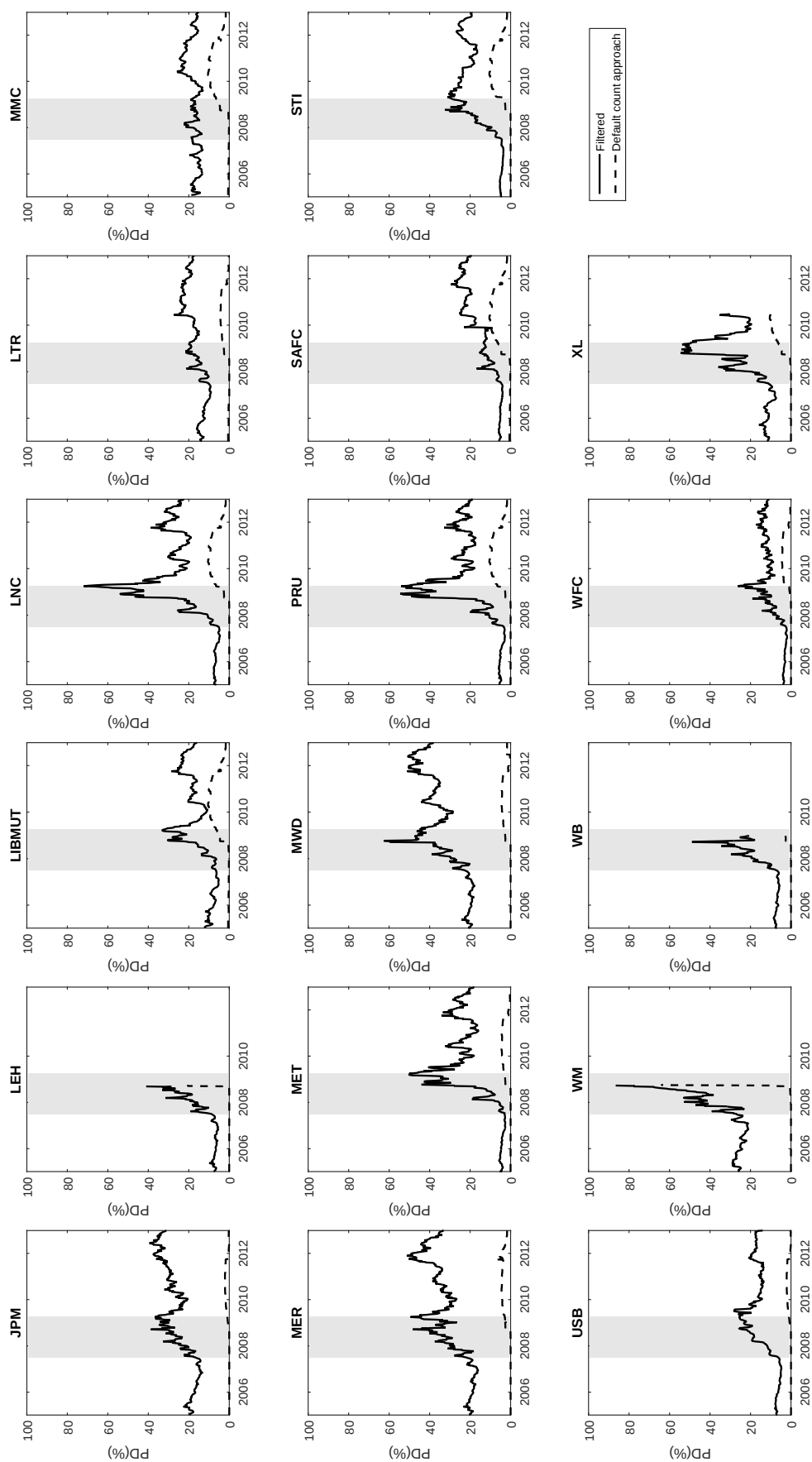


Figure C4: Filtered firm-specific probabilities of default for a 5-year time horizon along with default count approach probabilities of default, continued.

This figure shows the time series of firm-specific 5-year probabilities of default. Two methods are used to compute the default probabilities: the credit presented in the study (solid) and a default count approach (dashed). Filtered leverages and regimes are inferred using parameters estimated on a firm-by-firm basis.

Table C2: Descriptive statistics of correlation estimates.

	$\rho_{1,1}$		$\rho_{1,2}$		$\rho_{2,1}$		$\rho_{2,2}$		$\rho_{2,2} - \rho_{1,1}$			
	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD	Minimum	Maximum
ACE	0.548	0.191	0.295	0.242	0.374	0.183	0.835	0.128	0.287	0.197	-0.083	0.904
ALL	0.595	0.149	0.239	0.311	0.324	0.173	0.833	0.160	0.238	0.195	-0.241	0.645
AXP	0.617	0.158	0.289	0.150	0.312	0.138	0.826	0.143	0.210	0.205	-0.345	0.838
AIG	0.476	0.131	0.299	0.231	0.195	0.211	0.576	0.141	0.100	0.212	-0.380	0.529
AOC	0.448	0.182	0.205	0.334	0.361	0.226	0.827	0.158	0.380	0.203	-0.120	0.842
BSC	0.636	0.179	0.214	0.322	0.384	0.188	0.846	0.087	0.210	0.180	-0.068	0.606
BRK	0.516	0.174	0.265	0.275	0.193	0.211	0.818	0.143	0.302	0.199	-0.125	0.993
BACORP	0.513	0.208	0.327	0.187	0.246	0.294	0.809	0.110	0.297	0.227	-0.008	0.968
COF	0.553	0.140	0.332	0.242	0.292	0.225	0.844	0.108	0.292	0.156	0.032	0.596
SCH	0.226	0.217	0.197	0.278	0.139	0.390	0.800	0.166	0.574	0.296	-0.110	0.993
CB	0.614	0.172	0.261	0.196	0.345	0.431	0.824	0.115	0.210	0.177	-0.132	0.653
C	0.630	0.162	0.305	0.159	0.308	0.219	0.753	0.121	0.123	0.175	-0.262	0.543
DB	0.307	0.139	0.271	0.300	0.212	0.415	0.791	0.161	0.485	0.253	-0.735	0.857
FHLMC	0.359	0.159	0.350	0.224	0.407	0.203	0.757	0.133	0.398	0.178	0.059	0.857
FNMA	0.355	0.132	0.177	0.234	0.212	0.323	0.727	0.129	0.372	0.164	-0.031	0.668
GNWTH	0.396	0.113	0.248	0.111	0.241	0.121	0.685	0.176	0.290	0.215	-0.282	0.680
GS	0.587	0.183	0.205	0.313	0.279	0.240	0.817	0.122	0.230	0.161	-0.184	0.543
HIG	0.530	0.172	0.291	0.139	0.183	0.354	0.698	0.126	0.168	0.184	-0.247	0.582
JPM	0.397	0.187	0.228	0.146	0.244	0.206	0.830	0.116	0.433	0.211	-0.062	0.771
LEH	0.626	0.197	0.266	0.268	0.313	0.371	0.865	0.089	0.239	0.195	-0.153	0.657
LIBMUT	0.493	0.176	0.390	0.253	0.195	0.383	0.846	0.145	0.353	0.193	-0.062	0.852
LNC	0.557	0.231	0.413	0.153	0.421	0.229	0.780	0.155	0.224	0.257	-0.380	0.846
LTR	0.625	0.164	0.431	0.272	0.323	0.268	0.840	0.127	0.215	0.168	-0.193	0.607
MMC	0.373	0.191	0.382	0.260	0.402	0.326	0.834	0.167	0.461	0.215	-0.063	0.929
MER	0.592	0.191	0.179	0.230	0.357	0.252	0.796	0.115	0.205	0.195	-0.068	0.665
MET	0.540	0.176	0.249	0.163	0.272	0.178	0.757	0.095	0.217	0.163	-0.045	0.622
MWD	0.541	0.203	0.267	0.179	0.315	0.293	0.810	0.101	0.269	0.208	-0.144	0.759
PRU	0.584	0.156	0.246	0.179	0.290	0.123	0.810	0.145	0.226	0.209	-0.318	0.773
SAFC	0.418	0.138	0.499	0.328	0.439	0.233	0.584	0.175	0.167	0.211	-0.466	0.487
STI	0.453	0.170	0.201	0.233	0.307	0.257	0.761	0.206	0.308	0.269	-0.622	0.754
USB	0.510	0.162	0.294	0.202	0.321	0.253	0.610	0.220	0.100	0.274	-0.735	0.563
WM	0.604	0.180	0.271	0.424	0.331	0.339	0.653	0.148	0.049	0.254	-0.622	0.596
WB	0.497	0.159	0.351	0.309	0.201	0.313	0.480	0.234	-0.017	0.209	-0.430	0.491
WFC	0.418	0.169	0.335	0.186	0.254	0.129	0.808	0.120	0.390	0.165	0.013	0.685
XL	0.531	0.189	0.284	0.157	0.347	0.150	0.690	0.155	0.159	0.231	-0.430	0.974
Insurance/Insurance	0.600	0.155	0.333	0.229	0.315	0.247	0.799	0.155	0.199	0.171	-0.380	0.594
Banking/Banking	0.538	0.226	0.240	0.242	0.275	0.284	0.794	0.161	0.256	0.266	-0.735	0.968
Insurance/Banking	0.448	0.178	0.294	0.256	0.299	0.275	0.738	0.175	0.290	0.244	-0.466	0.993

[1] This table reports the averages and standard deviations (SD) of all pairwise correlations depending on the firms' regimes, i.e. both firms are in the stable regime ($\rho_{1,1}$), firms are in different regimes ($\rho_{1,2}$ and $\rho_{2,1}$), or both firms are in the highly volatile regime ($\rho_{2,2}$).

[2] Results are further aggregated along three groups: correlations across insurance firms (Insurance/Insurance), correlations across banking companies (Banking/Banking), and correlations between insurance and banking firms (Insurance/Banking).

Table C3: Second-stage parameter estimates: $\rho_{1,1}$ (lower triangle) and $\rho_{2,2}$ (upper triangle).

	ACE	ALL	AXP	AIG	AOC	BSC	BRK	BACORP	COF	SCH	CB	C	DB	FHLMC	FNMA	GNWTH	GS	HIG
ACE	1.00	0.89	0.92	0.51	0.96	0.89	0.94	0.85	0.91	0.93	0.96	0.78	0.84	0.78	0.76	0.78	0.85	0.78
ALL	0.80	1.00	0.92	0.48	0.97	0.95	0.95	0.84	0.92	0.95	0.95	0.71	0.85	0.83	0.80	0.81	0.84	0.80
AXP	0.69	0.75	1.00	0.60	0.92	0.86	0.91	0.89	0.97	0.92	0.88	0.81	0.83	0.78	0.75	0.79	0.79	0.75
AIG	0.60	0.67	0.40	1.00	0.34	0.76	0.47	0.57	0.56	0.28	0.62	0.66	0.84	0.70	0.71	0.34	0.70	0.68
AOC	0.67	0.62	0.64	0.46	1.00	0.90	0.93	0.83	0.93	0.95	0.95	0.74	0.91	0.87	0.83	0.78	0.85	0.75
BSC	0.60	0.63	0.73	0.47	0.39	1.00	0.92	0.89	0.85	0.88	0.86	0.87	0.86	0.84	0.84	0.69	0.92	0.73
BRK	0.63	0.68	0.72	0.43	0.49	0.51	1.00	0.83	0.89	0.90	0.91	0.74	0.89	0.72	0.76	0.83	0.83	0.84
BACORP	0.56	0.48	0.65	0.55	0.35	0.72	0.65	1.00	0.90	0.88	0.81	0.92	0.86	0.79	0.71	0.60	0.92	0.70
COF	0.60	0.65	0.79	0.52	0.46	0.73	0.56	0.62	1.00	0.91	0.90	0.84	0.84	0.85	0.83	0.74	0.93	0.75
SCH	0.02	0.30	0.08	0.39	0.10	0.65	-0.09	-0.09	0.32	1.00	0.89	0.76	0.76	0.73	0.68	0.77	0.86	0.57
CB	0.87	0.92	0.74	0.42	0.74	0.74	0.63	0.47	0.68	0.23	1.00	0.76	0.87	0.77	0.80	0.74	0.81	0.82
C	0.60	0.62	0.76	0.41	0.67	0.87	0.64	0.83	0.64	0.22	0.70	1.00	0.88	0.83	0.72	0.40	0.90	0.64
DB	0.25	0.34	0.36	0.39	0.10	0.40	0.30	0.12	0.28	0.14	0.31	0.43	1.00	0.79	0.76	0.80	0.89	0.76
FHLMC	0.22	0.38	0.62	0.24	0.31	0.38	0.38	0.20	0.32	0.36	0.50	0.40	-0.07	1.00	0.94	0.83	0.82	0.65
FNMA	0.27	0.30	0.50	0.33	0.23	0.46	0.30	0.32	0.41	0.11	0.36	0.54	0.25	0.88	1.00	0.82	0.81	0.64
GNWTH	0.48	0.47	0.43	0.53	0.27	0.44	0.37	0.35	0.41	0.09	0.49	0.40	0.28	0.27	0.42	1.00	0.66	0.64
GS	0.54	0.60	0.59	0.49	0.41	0.94	0.52	0.78	0.71	0.31	0.70	0.69	0.44	0.39	0.34	0.38	1.00	0.70
HIG	0.60	0.61	0.60	0.64	0.45	0.61	0.74	0.60	0.45	0.10	0.57	0.68	0.23	0.39	0.40	0.49	0.55	1.00
JPM	0.30	0.36	0.37	0.44	0.29	0.77	0.29	0.31	0.39	0.21	0.38	0.33	0.44	0.36	0.44	0.24	0.77	0.35
LEH	0.55	0.67	0.74	0.52	0.34	0.97	0.58	0.66	0.69	0.54	0.75	0.86	0.43	0.39	0.40	0.36	0.96	0.59
LIBMUT	0.75	0.70	0.56	0.58	0.61	0.52	0.61	0.45	0.47	0.07	0.69	0.46	0.19	0.17	0.21	0.44	0.47	0.64
LNC	0.68	0.70	0.72	0.80	0.64	0.31	0.74	0.68	0.61	-0.03	0.57	0.72	0.30	0.31	0.30	0.68	0.51	0.88
LTR	0.80	0.83	0.86	0.58	0.78	0.72	0.63	0.49	0.72	0.57	0.91	0.74	0.39	0.51	0.31	0.39	0.69	0.51
MMC	0.58	0.56	0.57	0.41	0.86	0.33	0.39	0.29	0.42	0.03	0.70	0.56	0.09	0.30	0.14	0.21	0.37	0.38
MER	0.62	0.63	0.67	0.55	0.38	0.91	0.64	0.81	0.72	0.17	0.61	0.85	0.44	0.34	0.36	0.43	0.94	0.64
MET	0.66	0.64	0.60	0.64	0.46	0.57	0.70	0.55	0.49	0.06	0.63	0.65	0.18	0.50	0.37	0.55	0.54	0.88
MWD	0.53	0.60	0.65	0.60	0.36	0.89	0.61	0.67	0.58	0.05	0.56	0.70	0.41	0.30	0.30	0.39	0.83	0.59
PRU	0.70	0.75	0.74	0.50	0.54	0.75	0.63	0.61	0.61	0.15	0.69	0.69	0.33	0.47	0.35	0.53	0.61	0.72
SAFC	0.46	0.57	0.48	0.53	0.32	0.47	0.54	0.40	0.44	0.49	0.54	0.55	0.28	0.33	0.19	0.33	0.27	0.43
STI	0.43	0.56	0.73	0.28	0.50	0.69	0.31	0.27	0.68	0.62	0.50	0.64	0.44	0.24	0.39	0.36	0.54	0.21
USB	0.41	0.52	0.65	0.12	0.42	0.70	0.52	0.48	0.64	0.46	0.75	0.66	0.68	0.14	0.33	0.44	0.39	0.43
WM	0.57	0.64	0.83	0.51	0.34	0.81	0.62	0.65	0.78	0.56	0.81	0.86	0.40	0.55	0.40	0.44	0.74	0.67
WB	0.37	0.54	0.62	0.37	0.26	0.67	0.40	0.76	0.45	0.40	0.50	0.82	0.31	0.31	0.37	0.40	0.63	0.57
WFC	0.36	0.41	0.46	0.40	0.32	0.65	0.36	0.54	0.43	0.25	0.40	0.54	0.21	0.42	0.40	0.23	0.69	0.40
XL	0.85	0.71	0.66	0.43	0.45	0.66	0.54	0.63	0.53	-0.16	0.82	0.69	0.35	0.41	0.38	0.47	0.59	0.39

[1] The table shows the second-stage correlation estimates obtained from CDS data from January 2005 to December 2012 by applying filtering techniques and quasi-likelihood maximization.

[2] More specifically, the following parameters are reported: $\rho_{1,1}$ (lower triangle) and $\rho_{2,2}$ (upper triangle).

Table C4: Second-stage parameter estimates: $\rho_{1,1}$ (lower triangle) and $\rho_{2,2}$ (upper triangle), continued.

	JPM	LEH	LIBMUT	LNC	LTR	MMC	MER	MET	MWD	PRU	SAFC	STI	USB	WM	WB	WFC	XL
ACE	0.90	0.90	0.96	0.89	0.98	0.96	0.83	0.83	0.82	0.91	0.77	0.92	0.69	0.66	0.37	0.84	0.83
ALL	0.91	0.95	0.97	0.92	0.97	0.97	0.82	0.85	0.85	0.93	0.75	0.89	0.37	0.76	0.30	0.81	0.82
AXP	0.93	0.89	0.93	0.89	0.91	0.94	0.88	0.83	0.87	0.95	0.63	0.90	0.60	0.58	0.28	0.87	0.83
AIG	0.62	0.81	0.54	0.42	0.53	0.35	0.61	0.68	0.72	0.45	0.57	0.63	0.65	0.34	0.67	0.62	0.57
AOC	0.90	0.89	0.95	0.86	0.97	0.98	0.82	0.76	0.79	0.89	0.76	0.87	0.73	0.71	0.24	0.85	0.79
BSC	0.89	0.98	0.91	0.88	0.89	0.93	0.84	0.79	0.92	0.94	0.56	0.77	0.68	0.81	0.84	0.86	0.78
BRK	0.63	0.94	0.92	0.89	0.93	0.93	0.82	0.84	0.82	0.89	0.70	0.86	0.72	0.69	0.27	0.82	0.84
BACORP	0.96	0.90	0.82	0.76	0.83	0.86	0.93	0.72	0.88	0.84	0.55	0.88	0.74	0.64	0.80	0.96	0.64
COF	0.94	0.88	0.92	0.83	0.91	0.93	0.91	0.81	0.92	0.90	0.59	0.88	0.70	0.81	0.54	0.91	0.78
SCH	0.91	0.91	0.92	0.82	0.93	0.96	0.84	0.65	0.81	0.92	0.52	0.89	0.80	0.72	0.32	0.85	0.81
CB	0.87	0.87	0.94	0.86	0.96	0.93	0.80	0.88	0.77	0.81	0.72	0.87	0.74	0.69	0.37	0.82	0.79
C	0.65	0.89	0.77	0.71	0.79	0.77	0.89	0.66	0.83	0.77	0.47	0.85	0.68	0.60	0.68	0.91	0.59
DB	0.84	0.86	0.86	0.83	0.81	0.76	0.86	0.81	0.86	0.78	0.65	0.66	-0.05	0.76	0.80	0.87	0.70
FHLMC	0.81	0.82	0.89	0.83	0.79	0.85	0.78	0.70	0.85	0.80	0.52	0.49	0.27	0.76	0.71	0.84	0.55
FNMA	0.79	0.78	0.86	0.65	0.75	0.81	0.75	0.71	0.82	0.76	0.50	0.36	0.37	0.73	0.61	0.80	0.49
GNWTH	0.68	0.85	0.86	0.77	0.77	0.81	0.63	0.76	0.68	0.88	0.82	0.45	0.16	0.65	0.29	0.51	0.70
GS	0.96	0.96	0.87	0.70	0.85	0.87	0.93	0.73	0.97	0.76	0.42	0.91	0.68	0.56	0.74	0.93	0.73
HIG	0.72	0.76	0.81	0.83	0.78	0.67	0.70	0.95	0.74	0.57	0.36	0.79	0.66	0.51	0.32	0.70	0.64
JPM	1.00	0.91	0.90	0.81	0.90	0.92	0.92	0.63	0.91	0.89	0.56	0.92	0.84	0.76	0.71	0.97	0.74
LEH	0.79	1.00	0.94	0.92	0.90	0.92	0.92	0.80	0.95	0.93	0.59	0.89	0.60	0.84	0.82	0.89	0.74
LIBMUT	0.39	0.40	1.00	0.94	0.96	0.95	0.83	0.87	0.85	0.94	0.72	0.88	0.78	0.76	0.21	0.69	0.84
LNC	0.15	0.32	0.80	1.00	0.90	0.87	0.72	0.89	0.78	0.88	0.69	0.81	0.61	0.68	0.15	0.74	0.80
LTR	0.29	0.74	0.65	0.58	1.00	0.96	0.82	0.83	0.83	0.93	0.78	0.92	0.78	0.69	0.36	0.83	0.83
MMC	0.14	0.27	0.50	0.56	0.76	1.00	0.86	0.75	0.83	0.93	0.77	0.90	0.80	0.76	0.17	0.86	0.83
MER	0.32	0.92	0.55	0.71	0.61	0.33	1.00	0.64	0.89	0.81	0.39	0.87	0.75	0.72	0.72	0.92	0.65
MET	0.35	0.58	0.63	0.87	0.59	0.41	0.53	1.00	0.77	0.76	0.77	0.81	0.62	0.64	0.48	0.75	0.76
MWD	0.16	0.96	0.48	0.77	0.55	0.34	0.91	0.60	1.00	0.79	0.55	0.91	0.58	0.59	0.74	0.89	0.74
PRU	0.36	0.68	0.63	0.90	0.78	0.42	0.61	0.81	0.60	1.00	0.84	0.75	0.74	0.83	0.28	0.84	0.65
SAFC	0.26	0.40	0.52	0.73	0.50	0.30	0.44	0.52	0.41	0.48	1.00	0.29	0.15	0.65	0.16	0.48	0.60
STI	0.17	0.69	0.46	0.30	0.70	0.25	0.47	0.20	0.39	0.51	0.44	1.00	0.80	0.14	0.45	0.90	0.77
USB	0.41	0.75	0.46	0.59	0.75	0.31	0.59	0.54	0.47	0.61	0.61	0.52	1.00	0.55	0.40	0.88	0.53
WM	0.57	0.83	0.39	0.31	0.73	0.16	0.78	0.66	0.73	0.48	0.27	0.76	0.73	1.00	0.61	0.69	0.34
WB	0.78	0.62	0.27	0.29	0.55	0.20	0.57	0.44	0.53	0.60	0.36	0.48	0.56	0.64	1.00	0.78	0.13
WFC	0.77	0.66	0.29	0.34	0.29	0.18	0.49	0.36	0.45	0.41	0.01	0.26	0.32	0.67	0.68	1.00	0.60
XL	0.54	0.66	0.77	0.58	0.75	0.31	0.57	0.58	0.45	0.60	0.32	0.40	0.36	0.63	0.56	0.59	1.00

Table C5: Second-stage parameter estimates: $\rho_{1,2}$ (lower triangle) and $\rho_{2,1}$ (upper triangle).

	ACE	ALL	AXP	AIG	AOC	BSC	BRK	BACORP	COF	SCH	CB	C	DB	FHLMC	FNMA	GNWTH	GS	HIG
ACE	1.00	0.34	0.30	0.55	0.06	0.27	0.16	0.57	0.50	0.20	0.55	0.43	0.49	0.56	0.22	0.30	0.35	0.33
ALL	0.29	1.00	0.32	0.45	-0.22	0.40	0.13	0.36	0.41	0.42	0.30	0.41	0.18	0.47	0.16	0.38	0.34	0.21
AXP	0.28	0.20	1.00	0.31	0.07	0.25	0.14	0.48	0.42	0.62	0.20	0.40	0.35	0.43	0.24	0.10	0.39	0.31
AIG	0.08	0.06	0.27	1.00	0.09	0.30	0.11	0.25	0.18	0.09	0.22	0.21	-	0.66	0.77	-0.10	0.22	0.20
AOC	0.55	0.49	0.19	0.43	1.00	0.13	0.39	0.58	0.34	0.15	0.63	0.34	0.39	0.32	0.35	0.27	0.40	0.64
BSC	0.30	0.30	0.31	0.31	0.31	1.00	0.35	0.31	0.31	0.31	0.24	0.29	0.37	0.50	0.20	0.30	-	0.27
BRK	-0.03	0.23	0.23	0.45	0.06	0.81	1.00	0.25	0.04	0.09	0.03	0.20	0.05	0.77	-0.05	-0.10	0.16	0.24
BACORP	0.30	0.31	0.30	0.31	0.17	0.31	0.02	1.00	0.30	0.17	-0.11	-0.02	-0.96	0.35	0.31	0.32	0.30	0.32
COF	0.66	0.31	0.30	0.29	-0.02	0.11	0.11	0.59	1.00	0.51	0.07	0.32	0.12	0.30	0.13	0.31	0.56	0.12
SCH	0.98	-0.30	0.31	0.02	0.30	-0.09	0.04	0.10	-0.46	1.00	-0.16	-0.27	-0.18	-0.02	-0.08	0.34	-0.26	-0.12
CB	0.30	0.30	0.31	0.30	-0.01	0.31	0.75	0.68	0.31	0.11	1.00	0.81	0.91	0.74	0.97	0.31	0.61	-0.89
C	0.30	0.31	0.31	0.03	0.31	0.31	0.55	0.35	0.30	0.13	0.30	1.00	0.50	0.74	0.31	0.30	0.29	0.30
DB	0.31	0.31	0.31	-	-0.89	-0.02	-0.20	0.28	0.97	0.32	-0.21	0.20	1.00	0.20	-0.33	0.31	-0.38	-0.01
FHLMC	-0.09	0.31	0.31	0.30	0.98	0.30	0.69	0.31	0.31	0.31	0.31	0.30	0.31	1.00	0.31	0.31	0.31	0.30
FNMA	-0.09	0.16	0.31	-0.53	-	0.31	0.83	0.02	0.31	0.33	-	0.14	0.31	0.20	1.00	0.31	0.77	-0.39
GNWTH	0.18	0.11	0.45	0.29	0.32	0.05	0.10	0.28	0.34	0.32	0.19	0.26	0.22	0.24	0.11	1.00	0.20	0.09
GS	0.31	0.27	0.30	0.38	-0.01	-0.97	-0.12	0.35	0.30	0.16	0.07	-0.01	0.52	0.40	0.00	0.28	1.00	0.11
HIG	0.19	0.03	0.33	0.36	0.16	0.31	0.30	0.22	0.29	0.12	0.22	0.27	0.30	0.53	0.31	0.31	0.17	1.00
JPM	0.30	-0.10	0.31	0.18	0.31	0.05	0.32	-0.07	0.30	0.01	0.10	0.30	0.17	0.39	0.22	0.31	-0.01	0.23
LEH	0.31	0.31	0.30	0.20	0.31	-	0.04	0.36	0.30	0.31	0.03	0.35	0.62	0.44	-0.02	0.31	-0.46	0.15
LIBMUT	0.84	0.75	0.30	0.59	0.25	0.49	0.19	0.42	0.68	0.50	0.51	0.35	0.48	0.63	0.44	0.06	0.27	0.61
LNC	0.41	0.13	0.48	0.33	0.38	0.30	0.36	0.39	0.48	0.41	0.47	0.39	0.30	0.30	0.31	0.30	0.30	0.30
LTR	0.30	0.30	0.30	0.47	0.29	0.92	0.38	0.81	0.43	0.64	0.33	0.80	0.43	0.83	0.27	0.30	0.77	0.44
MMC	0.32	0.45	0.15	0.31	0.32	0.42	0.26	0.70	0.70	0.63	0.36	0.42	0.49	0.47	0.43	0.08	0.63	0.31
MER	-0.01	0.30	0.31	0.33	0.03	-	-0.10	0.40	0.25	-0.03	0.02	0.24	0.42	0.27	0.03	0.30	0.60	0.16
MET	0.11	0.02	0.23	0.30	0.13	0.30	0.23	0.22	0.22	0.12	0.15	0.26	0.31	-0.25	0.30	0.18	0.18	0.43
MWD	0.20	0.96	0.22	0.23	0.17	0.51	0.11	0.29	0.23	0.05	0.16	0.28	0.46	0.38	0.02	0.31	0.27	0.14
PRU	0.28	0.23	0.32	0.30	0.26	0.13	0.27	0.31	0.39	0.17	0.29	0.29	0.22	0.43	0.24	0.37	0.24	0.42
SAFC	0.76	0.74	0.78	0.54	0.75	-0.11	0.73	0.56	0.60	0.49	0.59	0.67	0.26	0.27	-0.21	0.28	0.54	0.31
STI	0.18	0.19	0.31	0.44	-0.56	0.01	0.29	0.26	0.15	0.18	0.19	0.26	0.30	0.26	0.08	0.27	-0.03	0.26
USB	0.12	0.24	0.27	0.49	-0.08	-0.26	0.18	0.27	0.32	0.29	0.27	0.27	0.34	0.14	-0.05	0.46	0.33	0.38
WM	-	-0.96	-	0.21	-	0.08	-0.08	0.31	-	-	0.05	0.26	0.13	0.29	0.06	-	0.18	0.08
WB	0.31	0.31	-0.31	0.97	-	0.30	0.48	-	0.31	-0.18	0.31	0.49	0.31	0.42	0.31	0.30	0.31	0.68
WFC	0.31	0.31	0.31	0.31	0.30	0.31	0.42	0.44	0.31	0.00	0.30	0.05	-	0.13	0.31	0.31	0.31	0.30
XL	0.18	0.28	0.26	0.29	0.15	0.11	0.11	0.24	0.29	0.21	0.23	0.34	0.37	0.50	0.21	-0.01	0.16	0.30

[1] The table shows the second-stage correlation estimates obtained from CDS data from January 2005 to December 2012 by applying filtering techniques and quasi-likelihood maximization.

[2] More specifically, the following parameters are reported: $\rho_{1,2}$ (lower triangle) and $\rho_{2,1}$ (upper triangle).

[3] Given that some regime combinations are improbable, a few correlation estimates could not be found using our procedure. These values are removed from the table (e.g. -).

Table C6: Second-stage parameter estimates: $\rho_{1,2}$ (lower triangle) and $\rho_{2,1}$ (upper triangle), continued.

	JPM	LEH	LIBMUT	LNC	LTR	MMC	MER	MET	MWD	PRU	SAFC	STI	USB	WM	WB	WFC	XL
ACE	0.23	0.30	0.02	0.48	0.72	0.07	0.44	0.62	0.39	0.31	0.81	0.50	0.15	0.47	0.35	0.34	0.30
ALL	0.31	0.11	0.56	0.57	0.36	0.64	0.24	0.23	0.24	0.31	0.26	0.31	0.34	0.77	0.12	0.26	0.31
AXP	0.28	0.19	0.49	0.61	0.30	0.08	0.24	0.36	0.26	0.31	0.32	0.40	0.20	0.43	0.35	0.40	0.05
AIG	0.15	0.31	0.10	0.09	0.10	0.08	0.27	0.03	0.13	0.01	0.03	0.09	0.23	0.32	-0.41	0.16	0.22
AOC	0.43	0.26	0.41	0.59	0.62	0.11	0.40	0.64	0.40	0.17	0.63	0.96	0.20	0.31	0.33	0.48	0.42
BSC	0.31	0.79	-	0.60	0.31	0.97	-	0.31	0.76	0.31	0.45	0.52	0.61	0.31	0.19	0.38	0.31
BRK	0.26	0.72	0.02	0.67	0.10	0.05	0.03	0.29	0.22	0.30	0.29	-0.06	0.14	0.05	0.02	0.07	0.44
BACORP	0.10	0.32	-0.03	0.46	-0.12	0.02	0.30	0.31	0.31	0.30	0.44	0.30	0.16	0.31	0.93	0.19	0.31
COF	0.26	0.82	-0.10	0.39	-0.03	-0.03	-0.09	0.18	0.28	0.31	0.64	0.30	0.45	0.84	0.18	0.30	0.31
SCH	-0.18	-0.18	0.19	0.75	-0.51	0.91	-0.22	-0.17	-0.27	0.30	0.85	-	0.85	-0.22	-0.12	-0.01	0.79
CB	0.13	0.93	0.00	0.84	0.73	0.35	0.75	0.28	0.37	0.31	0.41	0.28	0.18	0.95	-0.72	0.18	0.31
C	0.30	0.31	-0.11	0.76	0.31	-0.11	0.30	0.31	0.32	0.31	0.32	0.31	0.50	0.31	0.31	0.17	0.30
DB	0.31	0.31	-0.77	0.18	-	0.39	0.97	0.09	0.96	0.31	0.37	0.30	0.50	0.31	0.08	0.17	0.31
FHLMC	0.31	0.30	-	0.42	0.30	0.91	0.32	0.30	0.31	0.31	-	0.30	0.81	0.31	0.31	0.30	0.29
FNMA	0.31	0.31	-	0.09	0.31	-	0.31	-	0.31	0.30	-	0.30	-0.55	0.31	-0.31	0.17	0.31
GNWTH	0.25	0.09	0.34	0.16	0.21	0.21	0.25	0.12	0.20	0.31	0.32	0.40	0.45	0.24	0.16	0.25	0.28
GS	0.31	0.31	-0.04	0.43	0.34	0.00	0.31	0.16	0.29	0.30	0.55	0.18	0.28	0.79	0.09	0.24	0.30
HIG	0.24	0.31	0.17	0.62	0.20	0.14	0.22	0.30	0.74	0.31	0.32	0.03	0.00	-0.81	0.94	0.16	0.28
JPM	1.00	0.10	-0.15	0.15	0.31	0.90	0.30	0.29	0.22	0.31	-	0.31	0.65	-0.22	0.24	0.02	0.31
LEH	0.31	1.00	-0.92	0.62	0.31	-	0.94	0.25	-0.54	0.30	0.69	0.54	0.43	0.31	0.20	0.28	0.31
LIBMUT	0.31	0.49	1.00	0.22	0.85	0.30	0.49	0.65	0.45	0.31	0.25	-	0.14	0.62	0.41	0.34	0.66
LNC	0.26	0.28	0.42	1.00	0.46	0.35	0.39	0.30	-0.06	0.31	0.67	0.07	0.63	0.29	0.31	0.24	0.65
LTR	0.27	0.89	-	0.86	1.00	0.31	0.68	0.48	0.73	0.31	0.15	0.31	0.35	0.04	0.37	0.45	0.31
MMC	0.44	0.44	0.05	0.47	0.50	1.00	0.61	0.36	0.57	0.79	0.72	0.95	0.18	0.63	0.48	0.45	0.45
MER	0.03	-0.60	-0.01	0.27	-0.02	0.07	1.00	0.29	0.71	0.31	0.51	0.32	0.18	0.31	0.13	0.25	0.30
MET	0.26	0.30	0.12	0.65	0.15	0.10	0.26	1.00	0.19	0.31	0.14	0.05	0.12	0.54	-	0.16	0.22
MWD	0.34	0.30	0.15	0.40	0.25	0.19	0.33	0.20	1.00	0.31	0.34	-0.02	0.31	0.69	0.11	0.20	0.31
PRU	0.25	0.12	0.32	0.50	0.24	0.19	0.20	0.41	0.12	1.00	0.11	0.06	0.30	0.42	0.09	0.26	0.31
SAFC	0.52	0.41	0.78	0.74	0.72	0.92	0.62	0.51	0.55	-0.58	1.00	0.89	0.47	0.11	0.31	0.55	0.70
STI	0.03	0.15	0.21	0.61	0.21	-0.10	0.21	0.28	0.11	-0.01	0.47	1.00	0.37	0.07	0.14	0.07	0.25
USB	0.33	0.46	0.31	0.52	0.13	0.03	0.30	0.41	0.32	0.29	0.33	0.31	1.00	0.52	0.26	0.22	0.25
WB	-	0.54	0.98	0.64	-	-	-0.12	0.15	-0.06	-	-	0.84	0.44	1.00	0.26	0.33	-
WM	0.30	0.30	-0.10	0.44	-0.11	0.84	0.31	0.58	0.30	0.30	-	-0.09	0.76	0.98	1.00	-	0.31
WFC	0.30	0.31	0.28	0.21	0.30	0.93	0.30	0.31	0.31	0.31	-	-	0.73	0.78	-	1.00	0.31
XL	0.25	0.23	0.20	0.44	0.37	0.10	0.24	0.33	0.26	0.31	0.94	0.33	0.32	0.43	0.41	0.27	1.00

Table C7: Linear and nonlinear Granger causality tests.

Panel A: Linear Granger causality.							
X = Insurance, Y = Banking				X = Banking, Y = Insurance			
L_X	L_Y	F -statistics	p -value	L_X	L_Y	F -statistics	p -value
1	5	6.199	0.000	5	3	5.013	0.002
Panel B: Nonlinear Granger causality using Diks and Panchenko (2006).							
X = Insurance, Y = Banking				X = Banking, Y = Insurance			
L_X	L_Y	DP-statistics	p -value	L_X	L_Y	DP-statistics	p -value
1	1	3.369	0.000	1	1	1.981	0.024
2	2	2.785	0.003	2	2	1.559	0.060
3	3	2.528	0.006	3	3	1.076	0.141
4	4	1.957	0.025	4	4	0.251	0.401
5	5	1.888	0.030	5	5	0.251	0.401
6	6	1.617	0.053	6	6	-0.309	0.621
7	7	1.589	0.056	7	7	-0.216	0.585
8	8	1.596	0.055	8	8	-0.677	0.751

[1] This table provides the various statistics and p -values associated with Granger causality tests. Broadly speaking, the null hypothesis is $H_0 : Y$ does not Granger-cause X . Therefore, the leftmost columns show whether the systemic risk of banks does Granger-cause systemic risk of insurers. Moreover, the rightmost columns show whether the systemic risk of insurers does Granger-cause systemic risk of banks.

[2] L_X and L_Y are the number of lags of X and Y respectively. For the linear case, they are determined using the Bayesian information criterion.

[3] Values in bold denote a significance level of 5%.

[4] We use a lead length of 1 and a bandwidth of 0.5 in Diks and Panchenko (2006). The results are robust to other choices.

For the opposite relationship (i.e. systemic risk of insurers Granger-causes the systemic risk of banks), the F -statistic is 5.013 and the null hypothesis is again rejected with a p -value lower than 1%.³⁰ This statistical conclusion would imply that the insurance subsector systemic risk Granger-causes that of the banking subsector.

In summary, our results show a compelling interconnectedness between both subsectors. This conclusion is similar to the findings of Chen et al. (2014).

C.5.2 Nonlinear Granger causality tests

The Diks and Panchenko (2006)'s Granger causality test requires the user to select some values such as the lead length, lag lengths L_X and L_Y , and bandwidth. Unfortunately, there is no method to define their optimal values. Following Hiemstra and Jones (1994) and Diks and Panchenko (2006), we set the lead length at 1 and $L_X = L_Y$, using a maximum of eight common lags. The bandwidth is set to 0.5.

Panel B of Table C7 shows the results of the nonlinear Granger causality tests. If we focus first on whether the systemic risk of banking firms Granger-causes the systemic risk of insurance companies, we find that we reject the null hypothesis for lag lengths below six at a confidence level of 5%. For the opposite relationship, we reject the null hypothesis for a lag length of one only.

Again, this would imply interconnectedness between both subsectors; however, connections from the banking subsector to the insurance subsector are somewhat stronger using the nonlinear statistical tests since we reject more often (i.e. for more lags).

³⁰We find five lags for banks and three for insurers using the same procedure as above.

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