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Credit and Systemic Risks in the Financial Services Sector

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joint work with M. Boudreault (UQAM),
D. Doljanu (National Bank) and G. Gauthier (HEC Montréal)

About the Speaker

- **Jean-François Bégin**, PhD, FSA, ACIA
- Assistant Professor

SFU

- **Simon Fraser University**
- Simon Fraser University is a public research university in British Columbia, Canada.
- SFU is consistently ranked as one of the top comprehensive universities in Canada.

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Motivation

- Financial crisis of 2008:
  - Highlighted **serious negative consequences of the interconnectedness** of large financial institutions.
  - Demonstrated the **lack of adequate credit and systemic risk monitoring** within the financial services industry.
  - Yet, even if the financial crisis is behind us, we still need to **comprehend its aftereffects**.
- Across all industries, **101 corporate issuers defaulted** ($281 billion) in 2008 (Moody's, 2009). For the sake of comparison, only 18 defaulted in 2007 ($6.7 billion).

Motivation, cont'd

- Billio et al. (2012): there are **four major determinants** of financial crises:
  1. Leverage.
  2. Losses.
  3. Linkages.
  4. Liquidity.

Introduction

- This paper focuses mainly on **credit and systemic risks** affecting both insurance and banking subsectors during the 2005–2012 period.
- We construct a multivariate credit risk model that accounts for the firm-specific financial health. It captures three major determinants: **leverage, losses and linkages**.
  - Firm-specific statistical regimes.
  - Pairwise regime-dependent correlations of leverage co-movements.
  - Endogenous stochastic recovery rates that are negatively related to the default probabilities.
- To estimate the model, we develop a **two-stage filtering procedure**.

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Leverage

- $A^{(i)}$ is the **market value of the *i*-th firm's assets**.
- $L^{(i)}$ is the **present value of the *i*-th firm's liabilities**.
- The *unobserved* **leverage ratio** is given by $X^{(i)} = L^{(i)}/A^{(i)}$ and log-leverage ratio process is

$$\log\left(X_t^{(i)}\right) = \begin{cases} \log\left(X_{t-1}^{(i)}\right) + \left(\mu^{(i)} - \frac{\left(\sigma_1^{(i)}\right)^2}{2}\right)\Delta + \sigma_1^{(i)}\sqrt{\Delta}\varepsilon_t^{(i)} & \text{if } s_t^{(i)} = 1 \\ \log\left(X_{t-1}^{(i)}\right) + \left(\mu^{(i)} - \frac{\left(\sigma_2^{(i)}\right)^2}{2}\right)\Delta + \sigma_2^{(i)}\sqrt{\Delta}\varepsilon_t^{(i)} & \text{if } s_t^{(i)} = 2 \end{cases}$$

where $\{\varepsilon_t^{(i)}\}_{t=1}^{\infty}$ are iid standardized Gaussian random variables.

Regime

- The *unobserved* **regime** $s_t^{(i)}$ prevailing on $((t-1)\Delta, t\Delta]$ is modelled as a time-homogenous Markov chain with transition probabilities

$$p_{jk}^{(i)} = \mathbb{P}\left(s_t^{(i)} = k \,\middle|\, s_{t-1}^{(i)} = j\right), \quad j,k \in \{1,2\}.$$

Linkage

- The model **captures the firms' interconnections through the correlation** between noise terms of log-leverage, i.e.

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

  with $\mathbf{s}_t \in \left\{s_t^{(i)}, s_t^{(j)}\right\}$, or $\mathbf{s}_t \in \{(1,1),(1,2),(2,1),(2,2)\}$.

- Four correlation values have to be estimated for each pair of firms depending on their specific regimes, i.e. $\rho_{\mathbf{s}_t}^{(i,j)} = \left(\rho_{1,1}^{(i,j)}, \rho_{1,2}^{(i,j)}, \rho_{2,1}^{(i,j)}, \rho_{2,2}^{(i,j)}\right)$.

Default Probabilities

- The **intensity process** is given by

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

where $\alpha^{(i)}, \theta^{(i)}, \beta^{(i)} > 0$.

Default Probabilities, cont'd

- In our discrete-time setting, the **default probability** is

$$\mathbb{P}\left(\tau^{(i)} \leq T \,\middle|\, \tau^{(i)} > t\right) = \mathbb{E}_t^{\mathbb{P}}\left[1 - \exp\left(-\sum_{s=t}^{T-1} H_s^{(i)} \Delta\right)\right]$$

where $\left\{H_t^{(i)}\right\}_{t=0}^{\infty}$ is the **default intensity process** and $\tau^{(i)}$ is the **default time**.

Recovery Rate

- Altman et al. (2005) argue the importance of having a recovery rate structure that is **inversely related** to the default probability.
- A proxy for the **recovery rate** is

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

  where $\kappa^{(i)}$ represents the **liquidation and legal fees** (fraction of the market value of assets at default).
- The leverage ratio process impacts on both the moment of default and the recovery rate, inducing a **negative correlation**.

Estimation

- Since leverage ratios and Markov regimes are unobservable variables, a **filtering procedure is needed**.
- We infer the latent variables **from observable CDS premiums**.
- Estimating all firms simultaneously is not numerically feasible. The estimation is thus **broken down into two stages**.
  1. First, the firm-specific parameters are estimated.
  2. The second stage then focuses on the interrelation between firms while keeping the firm-specific parameters fixed.

First Stage

- An extension of Tugnait's (1982) detection-estimation algorithm (DEA) is designed to filter both of our unobserved variables.
- The DEA is generalized to **account for nonlinearities** by running the unscented Kalman filter (UKF) of Julier and Uhlmann (1997) instead of the classic Kalman (1960) filter.

If We Can Observe the Regime

- The state equation is linear in $\log\left(X_t^{(i)}\right)$ and we know that $\log\left(X_t^{(i)}\right)$ is Gaussian given $\log\left(X_{t-1}^{(i)}\right)$ and $s_t^{(i)}$.
- We could therefore apply the UKF.
- The **filtered value** of $\log\left(X_t^{(i)}\right)$ based on the first t observations and the regime path $s_{0:t}^{(i)}$ is

$$\log\left(X^{(i)\,*}_{t|t,\,s_{0:t}^{(i)}}\right) = \mathbb{E}^{\mathbb{P}}\left[\log\left(X_t^{(i)}\right)\middle|\,\mathbf{CDS}^{(i)}_{\text{obs},1:t},\,s_{0:t}^{(i)}\right].$$

However, It Is Not the Case...

- The **filtered value** of $\log(X_t)$ based on the first t observations is

$$\log\left(X_{t|t}^{(i)*}\right) = \sum_{s_{0:t}^{(i)}} \log\left(X^*_{t|t,\, s_{0:t}^{(i)}}\right) \mathbb{P}\left(s_{0:t}^{(i)} \,\middle|\, \mathbf{CDS}_{\text{obs},1:t}^{(i)}\right),$$

  which is a sum over 2^t elements.

- A good approximation could be to take the 2^k most likely paths based on the latest regimes:

$$\log\left(X_{t|t}^{(i)*}\right) \approx \sum_{s_{1-k+1:t}^{(i)}} \log\left(X^*_{t|t,\, s_{1-k+1:t}^{(i)}}\right) \mathbb{P}\left(s_{1-k+1:t}^{(i)} \,\middle|\, \mathbf{CDS}_{\text{obs},1:t}^{(i)}\right),$$

  which is a sum over 2^k elements.

Second Stage

- For each pair of firms (i, j) and conditional on $\left\{\boldsymbol{\Theta}_1^{(i)}, \boldsymbol{\Theta}_1^{(j)}\right\}$, we build a likelihood function for $\boldsymbol{\Theta}_2^{(i,j)} = \left(\rho_{1,1}^{(i,j)}, \rho_{1,2}^{(i,j)}, \rho_{2,1}^{(i,j)}, \rho_{2,2}^{(i,j)}\right)$ using the DEA-UKF scheme.
- Dependence among firms must be captured endogenously, or **prior to the filtering process**.

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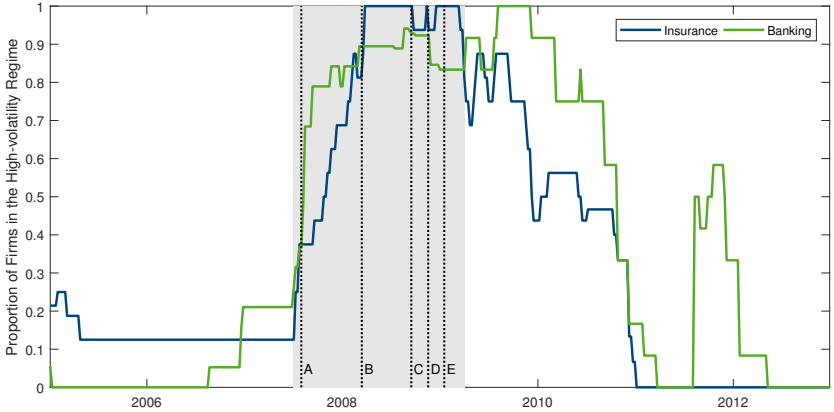
Data

- Results based on **35 firms** of the financial sector: 16 insurance companies and 19 banking firms.
- Weekly term structure of CDS premiums over **2005–2012**.
- Premiums of maturities of 1, 2, 3, 5, 7 and 10 years.
- Three time periods considered:
  - Pre-crisis: from 2005 to June 2007.
  - Crisis: from July 2007 to March 2009.
  - Post-crisis: from April 2009 to 2012.

Firms in the High-Volatility Regime



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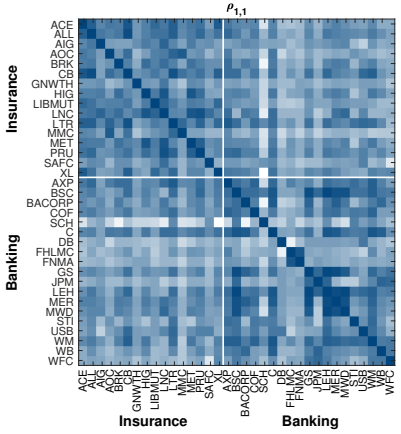
Heat Maps


$\rho_{1,1}$
Insurance
Banking
ACE
ALL
AIG
AOC
BRK
CB
GNWTH
HIG
LIBMUT
LNC
LTR
MMC
MET
PRU
SAFC
XL
AXP
BSC
BACORP
COF
SCH
C
DB
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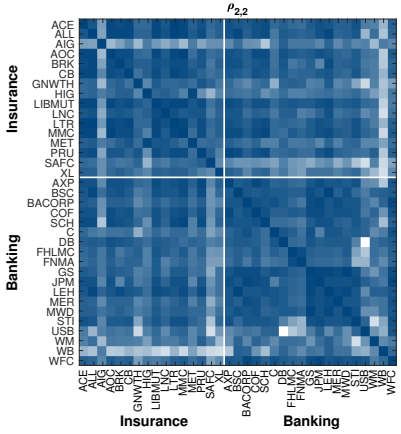
FNMA
GS
JPM
LEH
MER
MWD
STI
USB
WM
WB
WFC


$\rho_{2,2}$
Insurance
Banking
ACE
ALL
AIG
AOC
BRK
CB
GNWTH
HIG
LIBMUT
LNC
LTR
MMC
MET
PRU
SAFC
XL
AXP
BSC
BACORP
COF
SCH
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MER
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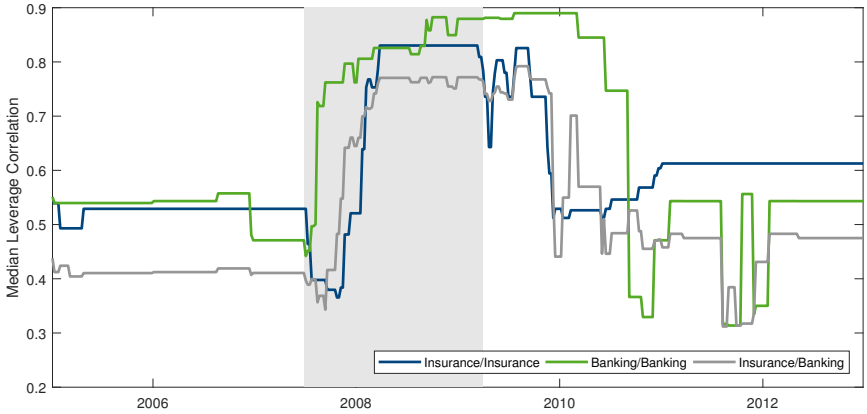
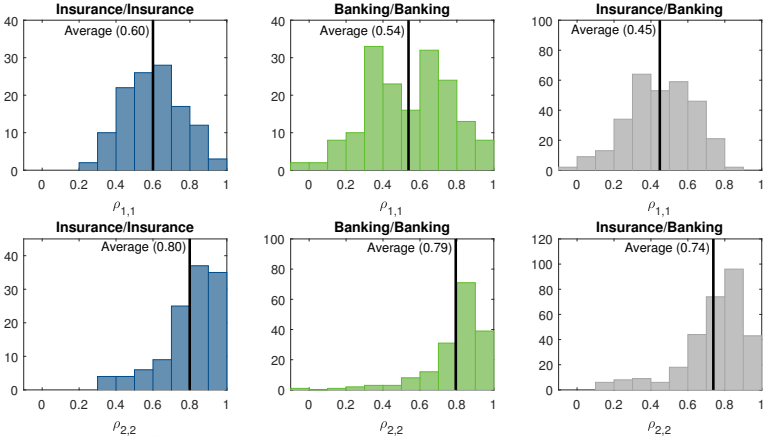
STI
USB
WM
WB
WFC

Median Leverage Correlation



Histograms of $\rho_{1,1}$ and $\rho_{2,2}$



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Systemic Risk

- Systemic risk is the **risk of collapse of an entire financial system** as opposed to risk associated with any one individual entity.
- It refers to the risks **imposed by interlinkages and interdependencies** in a system or market, where the failure of a single entity or cluster of entities can cause a cascading failure.

Definition

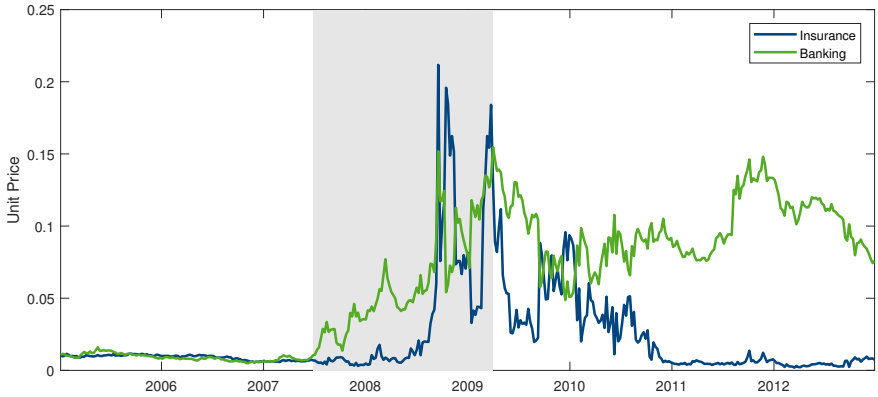
- The systemic risk measure is defined as the **expected value of a loss over a period of three months given that it is higher than the 99th percentile of the loss distribution** for each subsector:

$$\left(\sum_{i \in \mathrm{SS}} L^{(i)}_{t,t+3 \text{ months}} \right) \mathbf{1} \left(L_{t,t+3 \text{ months}} > \mathrm{VaR}_{0.99}(L_{t,t+3 \text{ months}}) \right),$$

  where $\mathrm{SS} \in \{\mathrm{Ins}, \mathrm{Bnk}\}$.

- The relative contributions *RSR* are scaled versions of the nominal price measures. We simply **divide the contributions by the sum of the total liabilities for each respective subsector**.

Systemic Risk Measure



Granger Causality Tests

Panel A: Linear Granger causality.

X = Insurance, Y = Banking				X = Banking, Y = Insurance			
L_X	L_Y	F-stat.	p-value	L_X	L_Y	F-stat.	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-stat.	p-value	L_X	L_Y	DP-stat.	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

Granger Causality Tests, cont'd

- 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.
- These results are **in line with the literature**.
  - Chen et al. (2014): 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.
  - Billio et al. (2012): they find that banks tend to have a much more important role in the transmission of shocks.

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Concluding Remarks

- **A Markov-switching hybrid credit risk model** is proposed.
- Our results indicate **an increase in correlation during the high-volatility regime**.
- There is **supportive evidence of increased systemic risk within the financial services sector during the last global crisis**.
- There is also a unidirectional causal effect from banks to insurers in terms of systemic risk.

Thank you very much for your attention!

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References

Acharya, V., R. Engle, and M. Richardson. 2012. Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review* 102:59–64.

Altman, E. I., B. Brady, A. Resti, and A. Sironi. 2005. The link between default and recovery rates: Theory, empirical evidence, and implications. *Journal of Business* 78:2203–2228.

Baek, E. G., and W. A. Brock. 1992. A nonparametric test for independence of a multivariate time series. *Statistica Sinica* pp. 137–156.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104:535–559.

Boudreault, M., G. Gauthier, and T. Thomassin. 2014. Contagion effect on bond portfolio risk measures in a hybrid credit risk model. *Finance Research Letters* 11:131–139.

Boudreault, M., G. Gauthier, and T. Thomassin. 2015. Estimation of correlations in portfolio credit risk models based on noisy security prices. *Journal of Economic Dynamics and Control* 61:334–349.

Chen, H., J. D. Cummins, K. S. Viswanathan, and M. A. Weiss. 2014. Systemic risk and the interconnectedness between banks and insurers: An econometric analysis. *Journal of Risk and Insurance* 81:623–652.

Diks, C., and V. Panchenko. 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control* 30:1647–1669.

Garzarelli, F. 2009. The 2007-09 credit crisis and its aftermath. *Working paper* pp. 1–27.

Granger, C. W. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37:424–438.

Hiemstra, C., and J. D. Jones. 1994. Testing for linear and nonlinear Granger causality in the stock price-volume relation. *Journal of Finance* 49:1639–1664.

Huang, X., H. Zhou, and H. Zhu. 2009. A framework for assessing the systemic risk of major financial institutions. *Journal of Banking and Finance* 33:2036–2049.

Joe, H., and J. J. Xu. 1996. The estimation method of inference functions for margins for multivariate models. *Working paper* pp. 1–22.

Julier, S. J., and J. K. Uhlmann. 1997. A new extension of the Kalman filter to nonlinear systems. In *Proc. of AeroSense: The 11th Int. Symp. on Aerospace/Defence Sensing, Simulation and Controls*.

Kalman, R. E. 1960. A new approach to linear filtering and prediction problems. *Journal of Basic Engineering* 82:35–45.

Maalaoui Chun, O., G. Dionne, and P. François. 2014. Detecting regime shifts in credit spreads. *Journal of Financial and Quantitative Analysis* 49:1339–1364.

Moody's. 2009. Corporate Default and Recovery Rates, 1920-2008. `http://v2.moodys.com/cust/content/content.ashx?source=StaticContent/Free%20Pages/Credit%20Policy%20Research/documents/current/2007400000578875.pdf`.

Mueller, P. 2008. Credit spreads and real activity. *Working paper* pp. 1–62.

Schönbucher, P. J. 2002. A tree implementation of a credit spread model for credit derivatives. *Journal of Computaional Finance* 6:1–38.

Tugnait, J. K. 1982. Detection and estimation for abruptly changing systems. *Automatica* 18:607–615.

Yuen, F. L., and H. Yang. 2010. Option pricing with regime switching by trinomial tree method. *Journal of Computational and Applied Mathematics* 233:1821–1833.

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Contributions

The contributions of this paper are threefold.

1. 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).
2. Then, **sector-wide credit risk is assessed** through linkages between comovements of firm leverages.
3. Finally, the **systemic risk measures of two subsectors**, namely insurance and banking, **are computed** and compared: we detect a unidirectional causal effect from banks to insurers when accounting for heteroskedasticity.

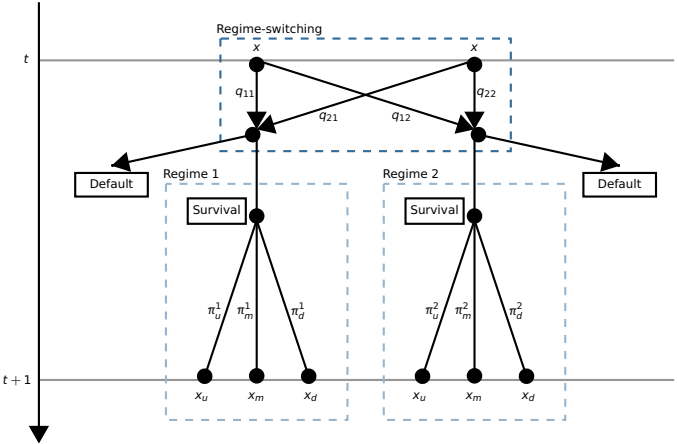
Change of Measure

- **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.
- We restrict the choices to those preserving the model structure by having **different drift and transition probabilities** under both measures $\mathbb{P}$ and $\mathbb{Q}$, meaning that the regime risk is priced.

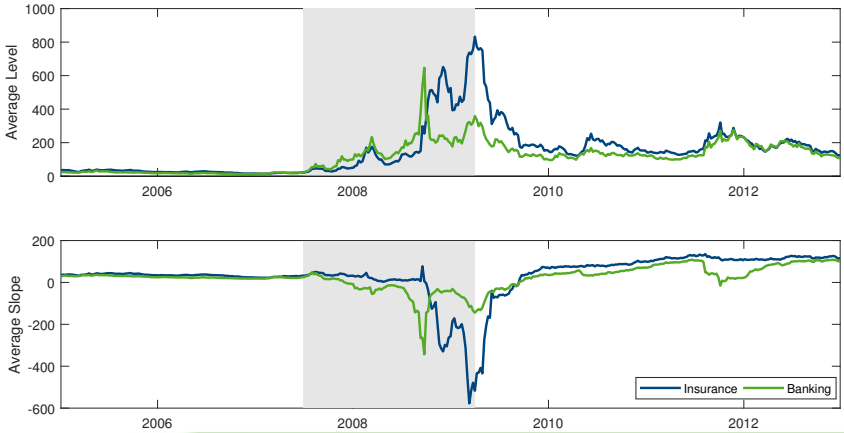
Trinomial Lattice Approach

- No closed-form solution for corporate bond prices and CDS premiums.
- A numerical scheme is used: it is based on extensions of Schönbucher (2002) and Yuen and Yang's (2010) trinomial lattice.
  - Schönbucher (2002): **adds an "artificial" branch** for default.
  - Yuen and Yang (2010): **same trinomial lattice for every regime, but change the weights**; the trinomial tree is recombining.

Trinomial Lattice Approach, cont'd



Data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1000
800
600
400
200
0
2006
2008
2010
2012
Average Slope
200
0
-200
-400
-600
2006
2008
2010
2012
Insurance
Banking

Parameter Estimates

	$\mu^{\mathbb{Q}}$(%)	$\mu^{\mathbb{P}}$(%)	σ_1	σ_2	q_{11} (%)	p_{11}(%)	q_{22}(%)	p_{22}(%)	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
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	β(%)	δ_1	δ_2	δ_3	δ_5	δ_7	δ_{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
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

Parameter Estimates, cont'd

	$\mu^{\mathbb{Q}}$(%)	$\mu^{\mathbb{P}}$(%)	σ_1	σ_2	q_{11} (%)	p_{11}(%)	q_{22}(%)	p_{22}(%)	κ
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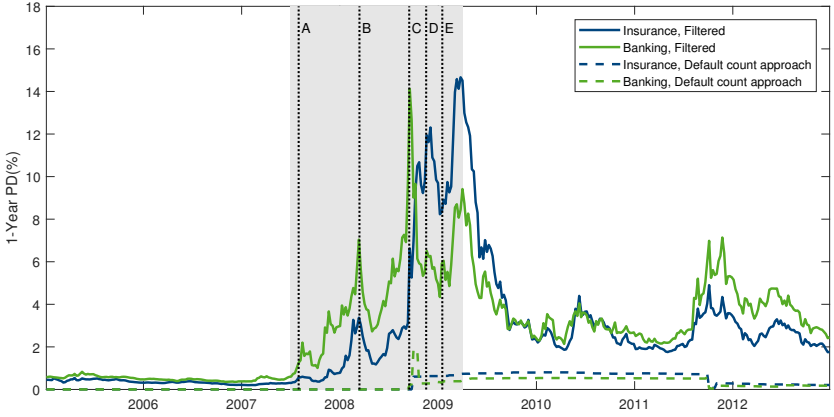
SD	3.138	0.099	0.281	0.058	0.036	0.023	0.019	0.028	0.026

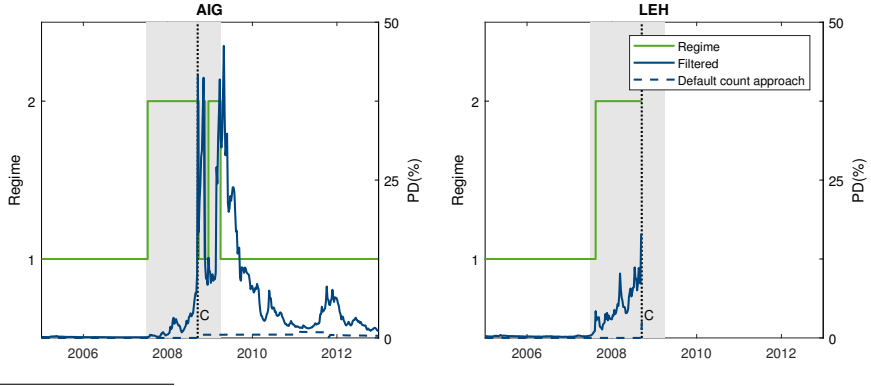
Firms in the High-Volatility Regime

- For both subsectors, there is some persistence in the proportion during the post-crisis era. This observation is **consistent with the literature**.
  - Maalaoui Chun et al. (2014).
  - Garzarelli (2009).
  - 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**.

Default Probabilities, cont'd



Default Probabilities, cont'd



C LEH files for Chapter 11 bankruptcy protection. MER is taken over by the BACORP. AIG almost defaulted the next day (September 15, 2008).

Default Probabilities, cont'd

	Pre-crisis		Crisis		Post-crisis	
Firm	Filtered	Default count	Filtered	Default count	Filtered	Default count
ACE	0.57	0.00	1.53	0.14	1.71	0.35
			⋮			
AIG	0.14	0.00	7.46	0.14	6.50	0.55
			⋮			
LEH	0.26	0.00	4.92	0.17	-	-
			⋮			
XL	0.46	0.00	7.70	0.27	4.92	1.04
Insurance	0.35	0.00	4.16	0.18	3.29	0.59
Banking	0.51	0.00	4.56	0.15	3.63	0.40

Default Probabilities, cont'd

- PDs computed using a default count approach tends to lag behind the market, which explains why the probabilities are smaller during the crisis than in its aftermath. They are also based on sector-wide aggregated data.
- On the other side, **CDS-implied default probabilities are forward looking** and strongly react at the onset of the financial crisis and during the European crisis of 2012.

Sample Breakdown

- To talk about dependence, we need to break the sample down into three categories.
  1. Correlations between the leverages of **two insurance firms**.
  2. Correlations between the leverages of **two banking firms**.
  3. Correlations between the leverages of **one insurance firm and one banking company**.

Definition

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**.

1. Generate a sample of losses for each firm $L^{(i)}_{t,t+3 \text{ months}}$ and compute the total losses across the firms: $L_{t,t+3 \text{ months}}$.
2. Compute the systemic risk measure (SR) for the financial service sector as the sample average of

$$L_{t,t+3 \text{ months}} \mathbf{1}\left(L_{t,t+3 \text{ months}} > \text{VaR}_{0.99}(L_{t,t+3 \text{ months}})\right),$$

where $\text{VaR}_{0.99}$ represents the 99th percentile of the total losses distribution.

Definition, cont'd

3. Calculate the systemic risk contribution (so-called nominal price, in millions) for each subsector:

$$\left(\sum_{i \in \mathrm{SS}} L^{(i)}_{t,t+3\text{ months}}\right) \mathbf{1}\left(L_{t,t+3\text{ months}} > \mathrm{VaR}_{0.99}(L_{t,t+3\text{ months}})\right),$$

where $\mathrm{SS} \in \{\mathrm{Ins}, \mathrm{Bnk}\}$.

Definition, cont'd

- The relative contributions *RSR* are scaled versions of the nominal price measures. 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**.
- Our measure is related to the systemic risk measure of Acharya et al. (2012).
- 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.

Systemic Risk Measure

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

Granger Causality Tests

- Let $\{X_t\}$ and $\{Y_t\}$ be two scalar-valued stationary time series.
- Let $F(X_t \mid \mathbf{I}_{t-1})$ be the conditional probability distribution of X_t given the bivariate information set $\mathbf{I}_{t-1}$ consisting of an L_x-length lagged vector of X_t (i.e. $\mathbf{X}_{t-L_x}^{L_x}$) and L_y-length lagged vector of Y_t (i.e. $\mathbf{Y}_{t-L_y}^{L_y}$).
- Given lags L_x and L_y, the time series $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ if
$$F(X_t \mid \mathbf{I}_{t-1}) = F\left(X_t \,\middle|\, \mathbf{X}_t^{L_x}\right).$$
- A well-known test for bivariate causality involves estimating a **linear** reduced-form vector autoregression.

Granger Causality Tests, cont'd

- Baek and Brock (1992) propose a nonparametric statistical method for uncovering **nonlinear** causal relations that, by construction, cannot be detected by traditional linear causality tests. It is used by Hiemstra and Jones (1994).
- Diks and Panchenko (2006) suggest an alternative nonparametric test that circumvents the problems associated with Hiemstra and Jones.

Granger Causality Tests, cont'd

- We test **whether a subsector's contribution could be used to forecast the other's systemic risk**.
- To do so, we use both linear and nonlinear Granger (1969) causality tests.
- Heteroskedasticity could lead to a substantial bias: we follow Chen et al. (2014) and deal with Gaussian noise processes extracted from a generalized autoregressive conditional heteroskedasticity model.