

Spillovers from Systemic Bank Defaults

Mark Mink* and Jakob de Haan†

*De Nederlandsche Bank

†De Nederlandsche Bank and University of Groningen

Federal Reserve System 'Day-Ahead' Conference
on Financial Markets and Institutions

2 January 2014

Motivation

“The collapse of Lehman Brothers [in September 2008] amply demonstrated that the disorderly failure of a global financial firm has strong spillovers across markets and affects financial stability and national economies around the world.”

Financial Stability Board, 2010

“The collapse of Lehman Brothers [in September 2008] amply demonstrated that the disorderly failure of a global financial firm has strong spillovers across markets and affects financial stability and national economies around the world.”

Financial Stability Board, 2010

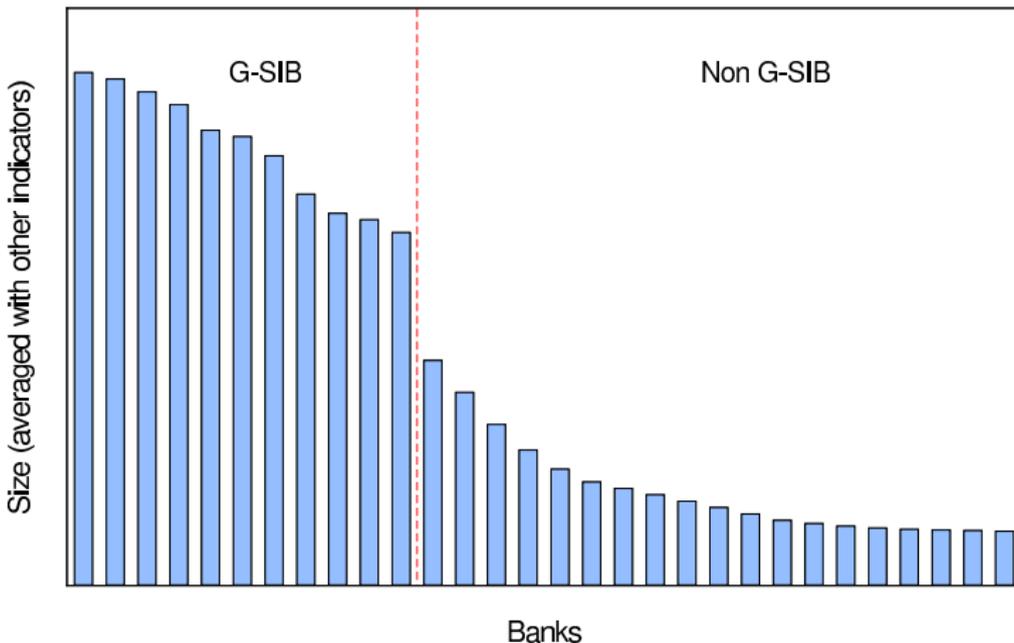
“The conclusion of the various Government actors [in November 2008] that Citigroup had to be saved was strikingly ad hoc. While there was consensus that Citigroup was too systemically significant to be allowed to fail, that consensus appeared to be based as much on gut instinct and fear of the unknown as on objective criteria.”

Special Inspector General for the Troubled Asset Relief Program, 2011

Motivation (2)

- Identifying systemic banks still comes with large uncertainty

The BCBS's approach to identify Globally Systemically Important Banks



Motivation (3)

- Problem: banking sector instability after a large bank's default can reflect spillovers or common shocks (domino analogy)
- An example of an adverse common shock is the news that governments will not rescue large banks that are about to fail
- The failure of a large bank such as Lehman could trigger both effects simultaneously
- We contribute to the literature (e.g. *CoVaR*, *SES*, *tail- β*) by focusing on the spillover effects from systemic bank defaults

- Spillovers between banks occur when the default of bank m causes bank n to suffer a loss:
 - due to direct exposures to bank m
 - due to write-downs after fire sales by bank m
 - due to panic runs triggered by the default of bank m
 - ...
- These actual losses are rarely observed, as failing systemic banks generally receive a bailout
- Bank n 's observed market value does however reflect *expected* losses from a default of m

Method (2)

- We model the change in bank n 's market value at time t as

$$y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$$

y_{nt} : change in bank n 's market value

α_n : bank-fixed effect

f_t : market factor (capturing common shocks)

p_{mt} : change in bank m 's default probability

ϵ_{nt} : error term

- γ_m is the average loss for the $N - 1$ banks if bank m defaults

Method (3)

- All variables are directly observed, except for the market factor

$$y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$$

- We use a three-step panel estimation technique:
 - 1 Estimate the model without including the market factor f
 - 2 Regress the residuals on time-fixed effects to obtain f
 - 3 Estimate the full model

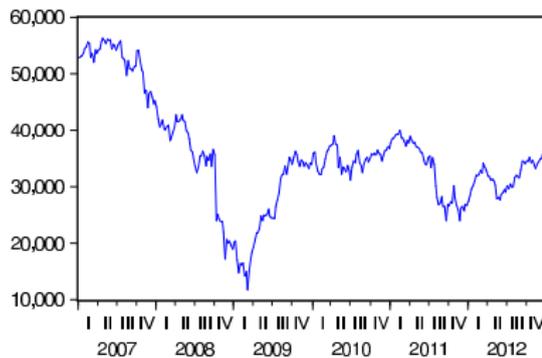
Note: this approach to obtain f leads us to underestimate common shocks and overestimate the role of spillover effects

- We repeat this procedure for 10,000 bootstrap replications

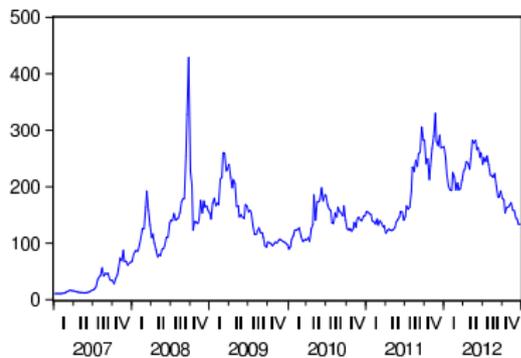
- Weekly data for 2007 – 2012
- Largest 100 banks from EU (59) and US (41)
 - Stock market capitalisation in January 2007 ranges from USD 6 bln. for Bankinter (ES) to USD 274 bln. for Citigroup (US)
- Calculate y_{nt} as the change in stock market capitalisation
- Calculate p_{mt} for G-SIBs only, as the change in 5-year:
 - credit default swap spreads (Datastream, 34 G-SIBs)
 - expected default frequencies (Moody's KMV, 37 G-SIBs)

Data (2)

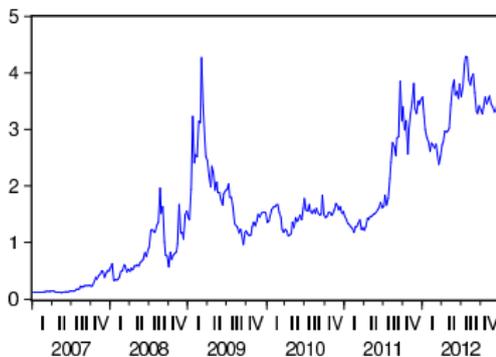
Market value (average over all banks; USD)



Credit default swaps spread (average over G-SIBs; bp.)



Expected default frequency (average over G-SIBs; %)



Results

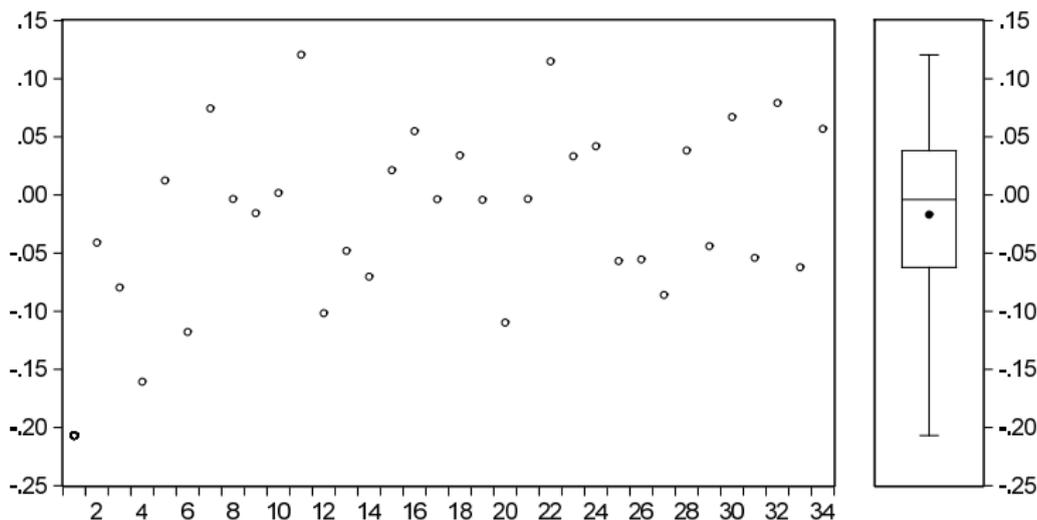
Regression equation: $y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$

	Fixed effects and market factor					Default risk (CDS)			Overall	
	α_n	$\alpha_n < 0$	β_n	$\beta_n > 0$	R^2	γ_m	$\gamma_m < 0$	R^2	R^2	N
(1) Full sample	0.00	2%	0.39	100%	0.16	-0.02	35%	0.21	0.38	25,901

Note: all variables have been standardised, so coefficients reflect correlations

Results (2)

- Some spillover coefficients have the wrong sign, there are no G-SIBs for which spillover coefficients are exceptionally large



Results (3)

Regression equation: $y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$

	Fixed effects and market factor					Default risk (CDS)			Overall	
	α_n	$\alpha_n < 0$	β_n	$\beta_n > 0$	R^2	γ_m	$\gamma_m < 0$	R^2	R^2	N
(1) Full sample	0.00	2%	0.39	100%	0.16	-0.02	35%	0.21	0.38	25,901
(2) Sub-samples based on location										
<i>n</i> and <i>m</i> from US	-0.01	2%	0.52	100%	0.27	-0.05	42%	0.24	0.51	9,687
<i>n</i> and <i>m</i> from EU	0.00	2%	0.49	98%	0.26	-0.02	50%	0.17	0.43	16,214

Note: all variables have been standardised, so coefficients reflect correlations

Results (3)

Regression equation: $y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$

	Fixed effects and market factor					Default risk (CDS)			Overall	
	α_n	$\alpha_n < 0$	β_n	$\beta_n > 0$	R^2	γ_m	$\gamma_m < 0$	R^2	R^2	N
(1) Full sample	0.00	2%	0.39	100%	0.16	-0.02	35%	0.21	0.38	25,901
(2) Sub-samples based on location										
<i>n</i> and <i>m</i> from US	-0.01	2%	0.52	100%	0.27	-0.05	42%	0.24	0.51	9,687
<i>n</i> and <i>m</i> from EU	0.00	2%	0.49	98%	0.26	-0.02	50%	0.17	0.43	16,214
(3) Sub-samples based on type										
<i>n</i> systemically important	0.00	6%	0.44	100%	0.19	-0.02	35%	0.27	0.46	9,219
<i>n</i> not systemically important	0.00	0%	0.39	100%	0.17	-0.03	38%	0.19	0.35	16,682

Note: all variables have been standardised, so coefficients reflect correlations

Results (3)

Regression equation: $y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$

	Fixed effects and market factor					Default risk (CDS)			Overall	
	α_n	$\alpha_n < 0$	β_n	$\beta_n > 0$	R^2	γ_m	$\gamma_m < 0$	R^2	R^2	N
(1) Full sample	0.00	2%	0.39	100%	0.16	-0.02	35%	0.21	0.38	25,901
(2) Sub-samples based on location										
<i>n</i> and <i>m</i> from US	-0.01	2%	0.52	100%	0.27	-0.05	42%	0.24	0.51	9,687
<i>n</i> and <i>m</i> from EU	0.00	2%	0.49	98%	0.26	-0.02	50%	0.17	0.43	16,214
(3) Sub-samples based on type										
<i>n</i> systemically important	0.00	6%	0.44	100%	0.19	-0.02	35%	0.27	0.46	9,219
<i>n</i> not systemically important	0.00	0%	0.39	100%	0.17	-0.03	38%	0.19	0.35	16,682
(4) Sub-samples based on time										
<i>t</i> before Lehman default	0.00	1%	0.36	100%	0.13	-0.01	25%	0.19	0.32	8,644
<i>t</i> after Lehman default	0.00	4%	0.39	96%	0.13	0.00	47%	0.30	0.43	17,257

Note: all variables have been standardised, so coefficients reflect correlations

Results (4)

Regression equation: $y_{nt} = \alpha_n + \beta_n f_t + \sum_{m \neq n} \gamma_m p_{mt} + \epsilon_{nt}$

	Fixed effects and market factor					Default risk (EDF)			Overall	
	α_n	$\alpha_n < 0$	β_n	$\beta_n > 0$	R^2	γ_m	$\gamma_m < 0$	R^2	R^2	N
(1) Full sample	0.00	0%	0.36	98%	0.14	-0.03	59%	0.24	0.38	25,901
(2) Sub-samples based on location										
<i>n</i> and <i>m</i> from US	0.00	0%	0.47	100%	0.20	-0.07	73%	0.30	0.50	9,687
<i>n</i> and <i>m</i> from EU	0.00	0%	0.45	100%	0.22	-0.03	68%	0.20	0.43	16,214
(3) Sub-samples based on type										
<i>n</i> systemically important	0.00	0%	0.41	100%	0.16	-0.03	57%	0.29	0.46	9,219
<i>n</i> not systemically important	0.00	0%	0.35	98%	0.14	-0.03	41%	0.22	0.35	16,682
(4) Sub-samples based on time										
<i>t</i> before Lehman default	0.00	0%	0.25	99%	0.06	-0.02	39%	0.25	0.31	8,644
<i>t</i> after Lehman default	0.00	2%	0.39	98%	0.11	-0.04	60%	0.32	0.42	17,257

Note: all variables have been standardised, so coefficients reflect correlations

Conclusion and caveats

- The analysis shows that bank market values:
 - are importantly driven by a common market factor
 - are hardly driven by individual G-SIBs' default risk
 - are importantly driven by the combined G-SIBs' default risk
- These results are robust to changing the sample and/or the measure of default risk
- G-SIBs thus seem to be systemically important as a group rather than on an individual basis
- If so, rescuing one G-SIB mainly stabilises other banks by confirming the existence of a government safety net

Conclusion and caveats (2)

- Potential caveats that may affect the results:
 - Government guarantees dampen changes in G-SIB default risk
 - But lower variation in these regressors does not bias the estimated spillover coefficients

Conclusion and caveats (2)

- Potential caveats that may affect the results:
 - Government guarantees dampen changes in G-SIB default risk
 - But lower variation in these regressors does not bias the estimated spillover coefficients
 - Common shocks are not measured directly
 - But our approach to estimate the market factor stacks the deck in favor of finding spillovers

Conclusion and caveats (2)

- Potential caveats that may affect the results:
 - Government guarantees dampen changes in G-SIB default risk
 - But lower variation in these regressors does not bias the estimated spillover coefficients
 - Common shocks are not measured directly
 - But our approach to estimate the market factor stacks the deck in favor of finding spillovers
 - Financial market prices may be wrong anyway
 - But that does not refute the result that bank market values were not driven by investors pricing spillover effects

Thank you for your attention!