

Bank Distress During the Credit Crisis: Contagion, or Common Shocks?

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Norges Bank Financial Stability Conference
2–3 September 2010

— work in progress, comments welcome! —

Motivation (1)

“The provision of [...] liquidity support undermines the efficient pricing of risk by providing *ex post* insurance for risky behaviour. That encourages excessive risk-taking, and sows the seeds of a future financial crisis.”

Mervyn King, Governor of the Bank of England
12 September 2007

Motivation (2)

- Despite this insight, fiscal and monetary authorities engaged in large scale rescue operations of financial intermediaries:
 - provision of emergency liquidity assistance
 - extension of deposit insurance
 - quantitative and qualitative monetary easing
 - purchase of 'troubled' assets
 - capital injections
 - nationalisations
 - ...
- Authorities this way aimed to protect depositors and avoid *contagion* (BIS 2009, p.24)

Motivation (3)

- Empirical research shows that banks indeed become unstable simultaneously:
 - autocorrelation in bank failures after controlling for macro-economic factors
 - reaction of banks' stock prices to adverse events
 - correlation between banks' stock returns
 - tail-correlation between banks' stock returns
 - decomposition of system-wide Value at Risk measures
 - ...
- But this correlation does not imply contagion, with instability of one bank *causing* the instability of another

Motivation (4)

- A smaller literature finds limited evidence for such contagion:
 - Calomiris & Mason (1997): banks fail primarily due to common asset value shocks
 - Aharony & Swary (1983): bank failures do not affect other banks' stock prices when they are due to bank-specific factors
 - Kho, Lee & Stulz (2002): stock markets distinguish between exposed and non-exposed banks when a crisis event occurs
 - Van Lelyveld & Liedorp (2006): limited potential for contagion through bilateral exposures on the interbank market
 - Taylor (2009): turmoil after the Lehman failure merely reflected uncertainty about government safety nets
- We aim to disentangle the impact of common shocks and contagion on banks' asset values during the crisis

Method (1)

- We define interbank contagion as the default of bank k causing bank i to suffer a loss:
 - from bilateral exposures on k (Allen and Gale 2000; Freixas, Parigi and Rochet 2000)
 - from write-downs induced by bank k 's fire-sales (Brunnermeier *et al.* 2009, Wagner 2010)
 - from premature asset liquidation due to bank runs triggered by confidence effects from k 's failure (Chen 1999)
 - from feedback effects due to a credit crunch in the real economy (Ashcraft 2005)
 - ...
- These actual losses are hard to observe, but bank i 's observed market value reflects the *expected* losses from a default of k

Method (2)

- The expected losses from bank k 's default are equal to the actual losses if k defaults, multiplied by the probability PD_k that this default occurs
- We thus model changes in bank i 's market value as

$$\Delta V_{it} = \alpha_i + \beta_i M_t + \sum_{k \neq i}^N \gamma_{ik} \Delta PD_{kt} + \epsilon_{it},$$

- market factor M_t reflects common asset value shocks
 - default probability PD_{kt} reflects contagion from k to i
 - idiosyncratic factor ϵ_{it} reflects bank-specific shocks
- $\gamma_{ik} \Delta PD_{kt}$ indicates the change in the expected loss for bank i associated with contagion from k 's potential future default

Method (3)

- We use the expression for ΔV_{jt} to substitute M_t out of the expression for ΔV_{jt} , which yields:

$$\Delta V_{i,t} = \alpha_{ij} + \beta_{ij}\Delta V_{j,t} + \gamma_{ij}\Delta PD_{j,t} + \epsilon_{ij,t} + \sum_{\substack{k \\ k \neq j}}^N \delta_{ik}\Delta PD_{k,t},$$

- β_{ij} indicates *correlation* between i and j 's asset values
 - γ_{ij} indicates *contagion* from j to i
 - δ_{ik} for control variables is a function of β_{ij} and γ_{jk}
- We estimate separate regressions for all i, j bank pairs
 - Rescue operations do not lead to underestimation of γ_{ij}

Data description (1)

- We calculate changes in asset values as

$$\Delta V_{it} = \Delta V_{it}^E + \Delta V_{it}^D \approx \Delta V_{it}^E,$$

where V_{it}^E and V_{it}^D are market values of equity and debt

- We calculate changes in default probabilities as

$$\Delta PD_{it} = \Delta \mathcal{N}(-DD_{it}) \approx 0.5 \Delta e^{-1/\sigma_{i,t+1}^E},$$

where $\sigma_{i,t+1}^E$ is the expected standard deviation of future equity returns, estimated using GARCH (see Byström, 2006)

- We also calculate the change in default risk as the change in CDS-spreads, i.e. ΔCDS_{it}

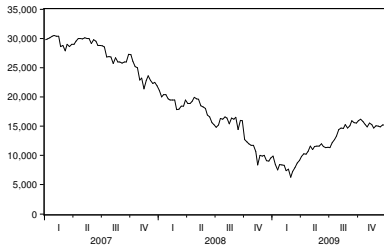
Data description (2)

- Sample period from January 2007 to January 2010
- Weekly data to reduce sensitivity to noise and time-lags
- 96 largest banks in US (25%), EU15, Iceland, Norway, and Switzerland (in terms of market capitalisation at 2007M01)
- Largest bank: Citigroup (US) $V^E = \text{EUR } 205 \text{ bln.}$
- Smallest bank: UCBH Holdings (US) $V^E = \text{EUR } 1.25 \text{ bln}$

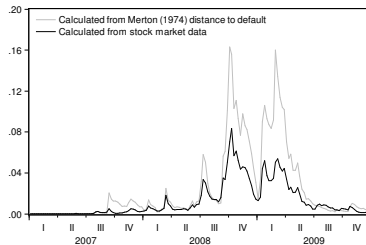
- ΔV and ΔPD are calculated from stock market data
- ΔCDS is the 5-year CDS-spread on senior debt (55 banks)

Data description (3)

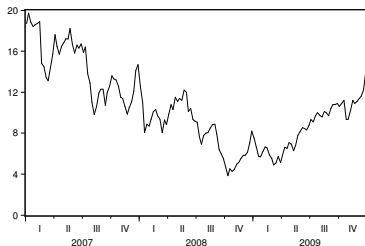
Average market value (EUR mln.)



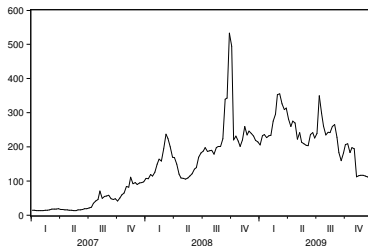
Average probability of default



Average distance to default



Average CDS-spread (basis points)



Empirical analysis (1)

Table: Results from ordinary least squares regressions

$$\frac{\Delta V_{i,t}}{V_i^{\max}} = \alpha_{ij} + \beta_{ij} \frac{\Delta V_{j,t}}{V_j^{\max}} + \gamma_{ij} \frac{\Delta PD_{j,t}}{PD_j^{\max}} + \epsilon_{ij,t} + \text{controls}$$

	Model with ΔPD	Model with ΔCDS
Correlation between i and j		
Average of all estimates	0.34	0.29
Frequency of t-stat(β_{ij}) > 1.645	0.84	0.76
Average estimate when t-stat(β_{ij}) > 1.645	0.38	0.35
Contagion from j to i		
Average of all estimates	0.00	-0.01
Frequency of t-stat(γ_{ij}) < -1.645	0.12	0.08
Average estimate when t-stat(γ_{ij}) < -1.645	-0.10	-0.25
Frequency that no-contagion model cannot be rejected	0.43	0.35

Table: Results from nonlinear least squares regressions

$$\frac{\Delta V_{i,t}}{V_i^{\max}} = \alpha_{ij} + \beta_{ij} \frac{\Delta V_{j,t}}{V_j^{\max}} + \gamma_{ij} \frac{\Delta PD_{j,t}}{PD_j^{\max}} + \epsilon_{ij,t} + \text{controls}, \text{ with } \gamma_{ij} < 0$$

	Model with ΔPD	Model with ΔCDS
Correlation between i and j		
Average of all estimates	0.32	0.28
Frequency of $t\text{-stat}(\beta_{ij}) > 1.645$	0.83	0.73
Average estimate when $t\text{-stat}(\beta_{ij}) > 1.645$	0.37	0.34
Contagion from j to i		
Average of all estimates	0.00	-0.06
Frequency of $t\text{-stat}(\gamma_{ij}) < -1.645$	0.12	0.09
Average estimate when $t\text{-stat}(\gamma_{ij}) < -1.645$	-0.10	-0.25
Frequency that no-contagion model cannot be rejected	0.55	0.45

Table: Results from nonlinear least squares regressions for ΔPD

$$\frac{\Delta V_{i,t}}{V_i^{\max}} = \alpha_{ij} + \beta_{ij} \frac{\Delta V_{j,t}}{V_j^{\max}} + \gamma_{ij} \frac{\Delta PD_{j,t}}{PD_j^{\max}} + \epsilon_{ij,t} + \text{controls}, \text{ with } \gamma_{ij} < 0$$

	Average of correlation estimates	Frequency of t-stat(γ_{ij}) < -1.645	Rejection freq. no-contagion model
Full sample	0.32	0.12	0.55
Sub-samples based on geography			
<i>j</i> from US, <i>i</i> from US	0.45	0.10	0.58
<i>j</i> from US, <i>i</i> from EU	0.27	0.17	0.59
<i>j</i> from EU, <i>i</i> from EU	0.35	0.11	0.57
<i>j</i> from EU, <i>i</i> from US	0.25	0.09	0.47
Sub-samples based on size			
<i>j</i> is large, <i>i</i> is large	0.45	0.14	0.46
<i>j</i> is large, <i>i</i> is small	0.31	0.10	0.66
<i>j</i> is small <i>i</i> is small	0.23	0.11	0.64
<i>j</i> is small <i>i</i> is large	0.30	0.12	0.45

Empirical analysis (4)

Table: Results from nonlinear least squares regressions for ΔCDS

$$\frac{\Delta V_{i,t}}{V_i^{\max}} = \alpha_{ij} + \beta_{ij} \frac{\Delta V_{j,t}}{V_j^{\max}} + \gamma_{ij} \frac{\Delta CDS_{j,t}}{CDS_j^{\max}} + \epsilon_{ij,t} + \text{controls}, \text{ with } \gamma_{ij} < 0$$

	Average of correlation estimates	Frequency of t-stat(γ_{ij}) < -1.645	Rejection freq. no-contagion model
Full sample	0.28	0.09	0.45
Sub-samples based on geography			
<i>j</i> from US, <i>i</i> from US	0.37	0.07	0.47
<i>j</i> from US, <i>i</i> from EU	0.23	0.07	0.48
<i>j</i> from EU, <i>i</i> from EU	0.32	0.09	0.51
<i>j</i> from EU, <i>i</i> from US	0.19	0.12	0.27
Sub-samples based on size			
<i>j</i> is large, <i>i</i> is large	0.34	0.08	0.33
<i>j</i> is large, <i>i</i> is small	0.26	0.07	0.63
<i>j</i> is small <i>i</i> is small	0.21	0.15	0.54
<i>j</i> is small <i>i</i> is large	0.22	0.12	0.20

Empirical analysis (5)

- Summary of findings on common asset value shocks:
 - Significant in about 80% of the regressions
 - More important for large banks or banks from the same region
- Summary of findings on interbank contagion:
 - Significant in only 10% of the regressions
 - Not more important for large banks or banks from the same region
 - The no-contagion model is not rejected for about 50% of the regressions
- Apparently, contagion explains only a limited part of banks' declining asset values

Discussion and implications

- If interbank contagion indeed was relatively limited:
 - Financial instability might arise primarily because of common shocks due to balance sheet homogeneity
 - Banks' opacity is more likely to be a problem, causing markets to interpret idiosyncratic shocks as common ones
 - Maintaining financial stability by regulating 'systemic institutions' might be a less fruitful exercise
 - Rescue operations might merely stabilise the system by their signalling effect
- These questions are open to further research