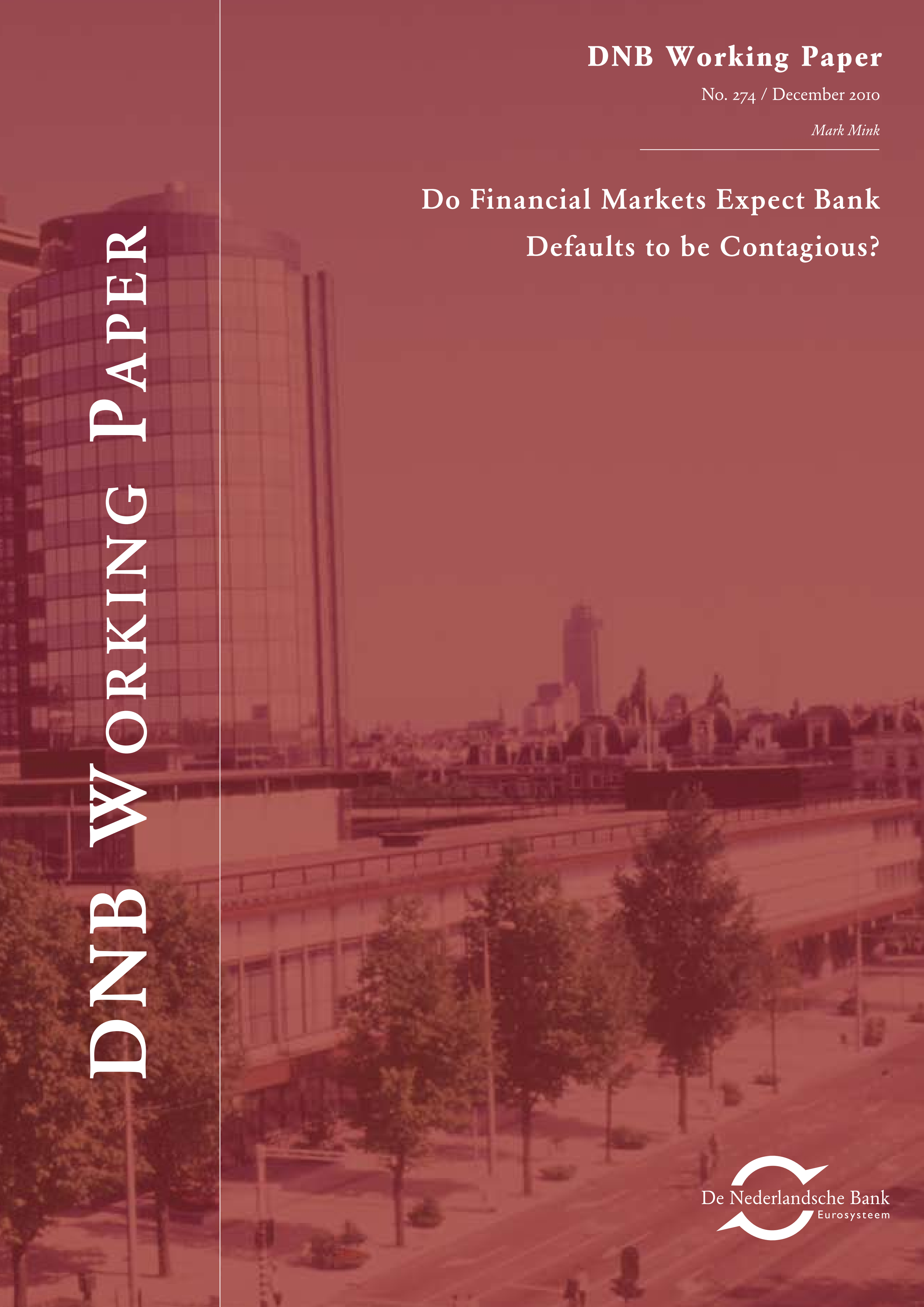

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Do Financial Markets Expect Bank Defaults to be Contagious?

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De Nederlandsche Bank
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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Do Financial Markets Expect Bank Defaults to be Contagious?

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Abstract

Simultaneous bank defaults are often attributed to interbank contagion, but can also be due to common shocks affecting banks with similar balance sheets. We disentangle both effects by realising that if financial markets expect a bank's default to be contagious, an increase in this bank's default probability should lower other banks' market valuations. When we regress changes in banks' market values on changes in other banks' default probabilities for the 2007–2009 financial crisis, we find no evidence for such an effect. This finding suggests that contagion risk has been overestimated, which has implications for financial regulation and crisis management.

Keywords: interbank contagion, financial stability, systemic banks, global financial crisis.
JEL codes: G01, G15, G21, G28

1 Introduction

"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, made this statement on 12 September 2007, only two days before he had to grant emergency liquidity assistance to Northern Rock. Ever since, fiscal and monetary authorities all over the world have engaged in massive rescue operations aimed at stabilising the global financial system. These rescue operations not only made use of conventional policy instruments such as the provision of emergency

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liquidity assistance, but also involved extending deposit guarantee schemes, insuring or purchasing 'troubled' assets, providing capital injections, and even nationalising financial intermediaries (see BIS 2009).

Fiscal and monetary authorities not only engaged in these rescue operations to protect (retail) depositors, but also to avoid contagion (BIS 2009, p. 24). These fears of contagion are based on the belief that the insolvency of one financial intermediary can have a destabilising impact on other intermediaries as well, which might destabilise the financial system as a whole and thereby disrupt the functioning of the real economy (De Bandt and Hartmann 2002). Avoiding these destabilising effects was the main motivation for the US government to rescue investment bank Bear Stearns and insurance company AIG, since the contagion effects that could be triggered by these companies' bankruptcies were believed to be particularly large (see Bernanke 2008, Federal Reserve Board 2008). Both cases illustrate how the current crisis lead financial regulators to become increasingly concerned with preventing contagion from the failure of so-called 'systemically important' financial institutions (see IMF 2009, Brunnermeier, Crockett, Goodhart, Persaud, and Shin 2009, Claessens, Herring, and Schoenmaker 2010).

The empirical literature on contagion has focused on the banking sector, and various studies confirm that banks tend to become unstable simultaneously.[1] However, the fact that distress situations coincide across banks does not imply there was contagion between them, with instability of one bank *causing* the instability of another. The coincidence can also be the result of common shocks hitting banks with similar balance sheets, for instance because they both invested in the American housing market, or because they have similar funding structures. Calomiris and Mason (1997) in fact conclude that "failures during the [1932 Chicago bank] panic reflected the relative weakness of failing banks in the face of a common asset value shock rather than contagion". Wall and Peterson (1990) find little evidence to support the concerns about bank runs around the 1984 Continental Illinois default. Aharony and Swary (1983) find that large bank failures only have an impact on other banks' stock prices when they are caused by problems

[1] Grossman (1993) and Hasan and Dwyer (1994) test for autocorrelation in bank failures after controlling for other macroeconomic factors. De Nicolò and Kwast (2001) examine the correlation between bank's stock returns, while Lehar (2005), Hartmann, Straetmans, and De Vries (2006), Bühler and Prokopczuk (2007), Gropp, Lo Duca, and Vesala (2009), and Zhou (2009) focus on correlation between returns in the tail of the distribution. Elsinger, Lehar, and Summer (2006), Adrian and Brunnermeier (2008), and Tarashev, Borio, and Tsatsaronis (2009) calculate measures of risk in the financial system as a whole, and decompose these into the contributions of individual banks.

whose revelation is correlated across banks, but not when the default is due to bank-specific factors such as internal fraud. Kho, Lee, and Stulz (2000) show that markets distinguish between exposed and non-exposed banks during a crisis, with losses of the exposed banks not spilling over to the unexposed ones. Finally, Furfine (2003), Upper and Worms (2004), and Van Lelyveld and Liedorp (2006) focus on direct exposures in the market for interbank loans, and find that the potential for contagion is rather limited.

These rejections of the contagion hypothesis seem to be at odds with policymakers' concerns as described above. Therefore, this study aims to disentangle the impact of contagion and common shocks on banks' market values during the credit crisis of 2007–2009. Our identification strategy is based on the presumption that if financial markets expect a bank's default to be contagious, as implied by the contagion hypothesis, an increase in their assessment of this bank's default probability should lead to a decline in other banks' market valuations. For a global sample of the one hundred largest banks, we therefore regress changes in banks' stock market values on changes in other banks' default risk. Since this analysis yields virtually no evidence for interbank contagion, it suggests that financial markets expect this risk to be of minor importance compared to the impact of adverse common shocks hitting multiple banks at the same time.

The implications of our findings could be substantial. If simultaneous distress in the banking sector is indeed mainly driven by common adverse shocks rather than by contagion, reducing the likelihood of system-wide instability would require the banking sector to become less homogeneous, with banks specialising in business activities instead of diversifying amongst them. At the same time, recent initiatives to identify 'systemically important' financial intermediaries become a much less fruitful exercise. The desirability of government rescue operations can be questioned as well, since rescuing one bank might not so much prevent contagion, but could merely stabilise other banks by signalling that, if needed, they will receive a bailout as well. If banks anticipate upon such bailouts in good times already, the additional risk-taking this induces renders the actual bailout nothing more than the transfer of a subsidy that was already factored into their business models and risk management policies. Such implicit guarantees then reduce market participants' regard for economic fundamentals, and indeed sow the seeds of a future financial crisis.

The remainder of this paper is organised as follows. Section 2 introduces our method, Section 3 describes the data used in the empirical analysis, and Section 4 presents our results. Section 5 discusses the implications of our findings, while the final section concludes.

2 Method

2.1 Modeling interbank contagion

Interbank contagion refers to the situation where the default of one bank causes other banks to suffer losses as well. The first, classic contagion channel is the interconnectedness between banks, for instance through loan and derivative exposures. An insolvent bank will default on its obligations will this way cause losses to other banks (see Allen and Gale 2000, Freixas, Parigi, and Rochet 2000). Second, **?** and Brunnermeier, Crockett, Goodhart, Persaud, and Shin (2009) describe how an outflow of funds can force one bank to engage in a fire sale of assets. Especially for illiquid assets such fire sales will depress market prices, which via mark-to-market accounting has to be reflected by write-downs on the value of similar assets on other banks' balance sheets. Third, contagion can arise from the opacity of banks' balance sheets, which requires investors to evaluate the value of their own bank's assets using public signals about the assets of other banks. One bank's default can this way trigger a run on other banks as well, with liquidity shortages and losses as a consequence (see Diamond and Dybvig 1983, Chen 1999).

The actual losses stemming from these contagion effects are hard to measure empirically, not the least because government rescue operations render defaults of large, potentially systemic banks a rarely observed phenomenon. We can however examine financial market data to measure the *expect* losses from contagion. If financial markets expect one bank's default to cause losses for other banks as well, an increase in their assessment of this bank's default probability should lower their valuations of these other banks. The reduction in these other banks' market valuation reflects the change in the expected value of contagious losses from all channels outlined above, including market players' expectations of any domino and feedback effects between banks.

Based on the above considerations we model the change in a bank's market value as

$$\Delta V_{i,t} = \alpha_i + \beta_i M_t + \textstyle\sum_{k \neq i}^{N} \gamma_{ik} \Delta PD_{k,t} + \epsilon_{i,t} \tag{1}$$

where Δ denotes the first-difference operator, $V_{i,t}$ indicates bank i's stock market valuation at time t, M_t indicates a market factor excluding any contagion effects, $PD_{k,t}$ equals the probability that bank k will default in the future, and $\epsilon_{i,t}$ captures idiosyncratic factors driving bank i's market value. When there is no contagion, the model thus relates the change in bank i's market value to a constant α_i and a market factor with loading

β_i, in line with the capital asset pricing model by Sharpe (1964). To take the effect of contagion into account, the model allows the market value to respond to changes in other banks' default probabilities. If the default of a bank k would cause contagious losses for bank i, the γ_{ik} parameter will be negative since an increase in PD_k then leads markets to price the higher expected value of these losses, causing market value V_i to decline.

Equation (1) makes clear that also when no actual bank defaults occur, we can still examine the impact of contagion on banks' market values. This is the case because forward-looking markets already price the expected costs of potential future bank defaults, by responding to changes in these banks' default probabilities. Since these default probabilities and the changes therein are about equal to zero in normal times and only become substantial during financial crises, our empirical model is in line with Forbes and Rigobon's (2002) definition of contagion as an increase in shock transmission during periods of crisis. While Forbes and Rigobon (2002) model contagion as a sudden increase in the correlation parameter β_{ij} during such periods, with the challenge being to distinguish this effect from an increase in the variance of the unobserved market factor M_t, we model contagion as a change in fundamentals, i.e. as a change in the losses expected from potential future bank defaults. When financial markets incorporate this information in banks' market valuations, this can lead to parallel declines in stock prices similar to the ones analysed by Forbes and Rigobon (2002).

2.2 Estimating the model

To estimate the model in Equation (1) we need data on the change in banks' market values V and default probabilities PD. We calculate changes in market values as the change in the value of banks' outstanding equity, and we follow Crosbie and Bohn (2003) to calculate probabilities of default by mapping banks' distances to default DD to the cumulative density function of the standard normal distribution. This distance to default can be calculated from the option-pricing framework by Black and Scholes (1973) and Merton (1974), but we prefer to follow Byström (2006) and use an alternative index that only requires the volatility of equity returns as an input.[2] In particular,

[2]Using equity volatility as a measure of default risk is quite common in the literature, see for instance Hall and Miles (1990), Saunders, Strock, and Travlos (1990), Esty (1998), Campbell, Lettau, Malkiel, and Xu (2001), Campbell and Taksler (2003), González (2005), Stiroh (2006), Zhang, Zhou, and Zhu (2009), and Laeven and Levine (2010).

we calculate the probability of default as

$$PD_{i,t} = \mathcal{N}\left(-DD_{i,t}\right) \approx \mathcal{N}\left(-1/\sigma_{i,t+1}\right), \tag{2}$$

where $\sigma_{i,t+1}$ equals the standard deviation of equity returns at time $t+1$, which we forecast using a GARCH model fitted to the time series with logarithmic equity returns. In this way we infer banks' market values V as well as their default probabilities PD directly from stock market data (see the Appendix for a more detailed discussion).

As an alternative to calculating model-based default probabilities from stock market data, we use spreads on banks' credit default swap (CDS) contracts as indicators of their default risk. These spreads have the advantage that they can be directly observed in financial markets. Moreover, they have been widely used as indicators of default risk by practitioners, policy makers and academics alike. A caveat associated with using these spreads is that they do not purely measure a bank's expected probability of default, but instead indicate the percentage premium to be paid for an insurance against the risk that bank j does not repay its outstanding debts in full. The spread therefore is also a function of the losses on bank j's debt given that it defaults, while it is also driven by factors such as market-wide risk aversion and the risk that the writer of the CDS-contract defaults himself.

The market factor M_t in Equation (1) cannot be observed directly. To arrive at a specification that contains only observable variables and can be estimated in a regression framework, we model the change in the market value of a bank j analogous to Equation (1), bring M_t to the left-hand side of this expression, and substitute the result in the original expression for ΔV_i to obtain

$$\begin{aligned} \Delta V_{i,t} &= \alpha_{ij} + \beta_{ij}\Delta V_{j,t} + \gamma_{ij}\Delta PD_{j,t} \\ &\quad -\beta_{ij}\gamma_{ji}\Delta PD_{i,t} - \sum_{k\neq i\neq j}^{N}\left(\beta_{ij}\gamma_{jk} - \gamma_{ik}\right)\Delta PD_{k,t} + \epsilon_{ij,t}, \end{aligned} \tag{3}$$

where $\alpha_{ij} = \frac{\beta_j\alpha_i - \beta_i\alpha_j}{\beta_j}$ and $\beta_{ij} = \frac{\beta_i}{\beta_j}$.[3] The parameter β_{ij} indicates to what extent changes in market values are *correlated* across banks i and j, and thus

[3] We would also arrive at this specification if we would model banks' market values as a function of multiple market factors instead of the single factor M_t in Equation (1). This still allows us to work with Equation (1), but changes our interpretation: the term $\beta_i M_t$ now equals the sum of all market factors weighted by the factor loadings for bank i, so that $\epsilon_{i,t}$ can be set to zero. Likewise, $\beta_j M_t + \epsilon_{j,t}$ equals the sum of all market factors weighted by the factor loadings for bank j, with $\epsilon_{j,t}$ being set orthogonal to M_t.

provides a measure of their sensitivity to common shocks. The parameter γ_{ij} indicates the losses for bank i that would be *caused* by the default of j, and thus measures the impact of contagion from bank j to bank i. Contagion effects thus differ from common shocks only in the sense that they are triggered by a change in banks' default risk, with both effects potentially having a widespread impact on banks' market values. The variable $\Delta PD_{i,t}$ accounts for reverse contagion from i to j, while the term $\Delta PD_{k,t}$ accounts for contagion from any third banks k to both i and j. The term $\epsilon_{ij,t}$ captures any remaining variation in bank i's market value.

When estimating the model in Equation (3) we are interested in the coefficients for the variables $\Delta V_{j,t}$ and $\Delta PD_{j,t}$, and include the other variables merely as controls. To reduce the number of coefficients to be estimated, we do not include all $n-2$ $\Delta PD_{k,t}$ variables as regressors, but instead include an index of the average change in all default probabilities at time t, denoted as $\Delta PD_{.,t}$. To increase the number of observations available to estimate the contagious impact of bank j's potential default on the other banks in the sample, we assume that this impact is the same across banks so that we can estimate a common coefficient $\gamma_{.j}$ across all cross-sections. We thus use pooled ordinary least squares to estimate the regression equation

$$\Delta V_{i,t} = \alpha_{ij} + \beta_{ij}\Delta V_{j,t} + \gamma_{.j}\Delta PD_{j,t} + \delta_{ij}\Delta PD_{i,t} + \zeta_{ij}\Delta PD_{.,t} + \epsilon_{ij,t}, \quad (4)$$

where, apart from the $\gamma_{.j}$ parameter, all coefficients are estimated on a cross-section specific basis. When we estimate this pooled regression, we obtain coefficients for the degree of correlation and contagion between bank j and the other banks in the sample. By including a different bank j and re-estimating the equation, we obtain such coefficients for each bank in the sample.

The estimates of the contagion coefficients are not affected by government bailouts of bank j, since the observed fluctuations in j's default probability and CDS-spread are already conditional upon the prospect of such rescue operations taking place. However, the contagion coefficients could be underestimated due to governments intending to mitigate the contagious impact of bank j's default through for instance providing additional liquidity to the system or buying troubled assets. However, changes in the prospect of such mitigating measures drive market values and CDS-spreads in opposite directions. As this inverse relationship is also implied by the contagion hypothesis, our omission of such changes from the regression equation could also cause the contagion coefficient to be overestimated.

3 Data description

To calculate the model variables we use data on banks' stock market values between January 1st 2007 and December 31st 2009, obtained from Thompson Datastream. Table 1 reports the 96 banks that we include in the analysis, of which 26 are located in the United States and 60 are from countries in the European Union. Our selection of banks covers the largest part of these region's banking 'systems'.[4] We calculate $\Delta V_{i,t}$ as the weekly change in these banks' stock market values, expressed in local currencies (see Mink 2009). By focusing on weekly data, our analysis is less sensitive to noise in the market returns or to any time lags in the response of market values to changes in default probabilities. We calculate $\sigma_{i,t+1}$ as the one-period ahead forecast from a GARCH(1,1) model fitted to weekly logarithmic equity returns.[5] We obtain the data on 5-year CDS-spreads on senior debt from Thompson Datastream for a sub-sample of fifty five banks, which in Table 1 are indicated with an asterisk.

Figure 1 shows the development over time of the cross-sectional averages of banks' market values, probabilities of default, and CDS-spreads. The upper panel illustrates that banks' market values have substantially declined over the 2007-2008 period. During the second and third quarter of 2009 market values have recovered somewhat, while thereafter they remained more or less stable. The middle panel shows that probabilities of default were especially volatile in the aftermath of the Lehman Brothers default. The graph illustrates how default risk can be absent during normal times, but can become quite real during times of crisis. By the end of 2009, the reported default probabilities have returned to their pre-crisis

[4]We select banks that are classified as Bank Holding & Holding Companies, Commercial Banks, Cooperative Banks, Investment Banks, Real Estate/Mortgage Banks, and Savings Banks, with leverage $D/(D+V)$ at least equal to 0.85 by the end of 2006 (where D equals the book value of debt). We also keep Bank of America, whose leverage equals 0.847 at the time. We limit the set of countries to the EU-15, Iceland, Norway, Switzerland, and the United States, and remove banks from the sample for which shares were not actively traded during all trading days of January 2007. Finally, we exclude Bank Austria Creditanstalt and Bayrische Hypo- und Vereinsbank (both part of UniCredit), Banca Lombarda (part of UBI Banca), BHW Holding (part of Deutsche Postbank), Depfa bank (part of Hypo Real Estate), Commerce Bancorp (part of TD bank), and Banca CR Firenze (largely owned by Intesa Sanpaolo).

[5]We calculate the weekly logarithmic returns as the sum of absolute daily logarithmic returns, where we interpolate 0.25 percent of the daily observations to control for unexpectedly large changes in volatility (as would result from sudden capital injections). The days for which we interpolated the data were selected as those for which fitting a GARCH(1,1)-model yielded the largest standardised residual.

Table 1: Overview of banks included in the sample

Bank	Country	Market value	Bank	Country	Market value
Citigroup*	US	207,814	Anglo Irish Bank Corporation (until 15/01/2009)*	IE	11,333
Bank of America*	US	182,048	Deutsche Postbank*	DE	10,453
HSBC Holdings*	GB	160,442	Banco de Sabadell	ES	10,377
JP Morgan Chase & Co.*	US	127,221	Banco Comercial Português*	PT	10,112
UBS*	CH	97,002	Crédit Industriel et Commercial (CIC)	FR	10,096
Royal Bank of Scotland Group*	GB	93,459	Sovereign Bancorp (old) (until 30/01/2009)	US	9,117
Banco Santander*	ES	88,436	CIT Group (until 01/11/2009)*	US	8,397
BNP Paribas*	FR	76,903	Banco Popolare	IT	8,163
ING Groep*	NL	74,067	LBB Holding (Landesbank Berlin Holding)	DE	7,955
Barclays*	GB	71,045	Eurohypo (until 25/07/2008)	DE	7,714
UniCredit*	IT	69,161	Alliance & Leicester (until 13/10/2008)*	GB	7,422
Wachovia (until 29/09/2008)*	US	68,374	Northern Rock (until 18/02/2008)*	GB	7,389
Morgan Stanley*	US	64,852	UBI Banca	IT	7,172
Banco Bilbao Vizcaya Argentaria	ES	64,788	Comerica Incorporated	US	7,078
Goldman Sachs Group*	US	64,457	Banco Espirito Santo*	PT	6,810
Credit Suisse Group*	CH	64,401	Kaupthing Bank (until 06/10/2008)*	IS	6,597
HBOS (until 13/10/2008)*	GB	63,405	Swiss Life Holding	CH	6,416
Merrill Lynch & Co. (until 05/12/2008)*	US	62,300	Hypo Real Estate Holding (until 06/10/2008)	DE	6,391
Société Générale*	FR	59,288	Banca Popolare di Milano*	IT	5,458
Deutsche Bank*	DE	52,962	Bankinter	ES	4,644
Lloyds Banking Group*	GB	47,939	Banco BPI	PT	4,492
Crédit Agricole*	FR	47,705	Bradford & Bingley (until 29/09/2008)*	GB	4,443
ABN Amro Holding (until 25/04/2008)*	NL	47,162	Banca popolare dell'Emilia Romagna	IT	4,352
Fannie Mae (until 07/09/2008)	US	43,970	Huntington Bancshares	US	4,285
Fortis (until 04/10/2008)*	BE	42,117	First Horizon National Corporation	US	3,949
Freddie Mac (until 07/09/2008)	US	35,776	Banco Pastor	ES	3,860
Metlife*	US	34,063	SNS Reaal	NL	3,857
KBC Group	BE	34,054	Investec	GB	3,722
Washington Mutual (until 26/09/2008)	US	32,649	Banca Italease (until 09/11/2009)	IT	3,691
Prudential Financial*	US	31,619	Glitnir Bank (until 06/10/2008)*	IS	3,569
Lehman Brothers Holdings (until 15/09/2008)*	US	31,441	Jyske Bank (Group)	DK	3,334
Standard Chartered*	GB	30,767	Landsbanki (until 06/10/2008)*	IS	3,136
Nordea Bank*	SE	30,273	Emporiki Bank of Greece	GR	3,085
Natixis*	FR	25,912	CREDEM	IT	3,017
Dexia*	BE	23,839	IKB Deutsche Industriebank*	DE	2,576
Danske Bank*	DK	23,525	Sydbank	DK	2,535
Countrywide Financial Corporation (Old) (until 11/01/2008)*	US	20,019	IndyMac Bancorp (until 11/07/2008)	US	2,430
Allied Irish Banks*	IE	19,828	Astoria Financial Corporation	US	2,270
Commerzbank*	DE	18,894	Pohjola Bank	FI	2,024
Erste Group Bank	AT	18,319	Credito Bergamasco	IT	1,870
Bank of Ireland*	IE	17,076	Wüstenrot & Württembergische	DE	1,738
Skandinaviska Enskilda Banken*	SE	15,951	Downey Financial (until 21/11/2008)	US	1,535
Svenska Handelsbanken*	SE	14,585	South Financial Group	US	1,519
Bear Stearns Companies (until 17/03/2008)*	US	14,500	Aareal Bank	DE	1,507
DnB Nor	NO	14,362	Valiant Holding	CH	1,415
Swedbank*	SE	14,166	First Citizens BancShares	US	1,347
Banca Monte dei Paschi di Siena*	IT	12,031	BANIF SGPS	PT	1,325
BANESTO*	ES	11,637	UCBH Holdings (until 06/11/2009)	US	1,261

Note: market values refer to the value of banks' equity by the end of 2006, reported in millions of euro; an asterisk indicates data on CDS-spreads is available.

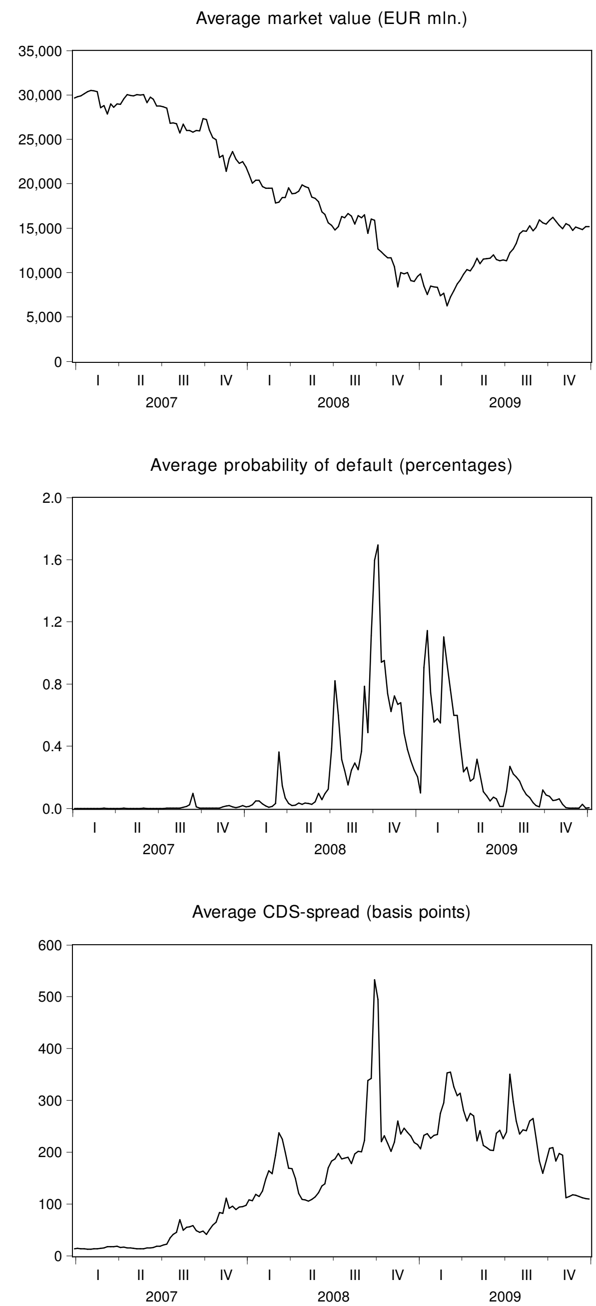
Table 2: Correlation between the regression variables

	Minimum	Average	Maximum
Cor($\Delta V_i, \Delta PD_i$)	-0.85	-0.02	0.68
Cor($\Delta V_i, \Delta CDS_i$)	-0.81	-0.32	0.04
Cor($\Delta PD_i, \Delta PD_j$)	-0.71	0.12	1.00
Cor($\Delta CDS_i, \Delta CDS_j$)	-0.62	0.39	0.97
Cor($\Delta PD_i, \Delta CDS_i$)	-0.38	0.04	0.97

levels. The bottom panel of the figure shows the average spread on banks' CDS-contracts. These spreads differ substantially from the observed default probabilities, although both start to increase around mid-2007 and on several occasions peak simultaneously. The differences between both indicators probably reflects that they measure somewhat different concepts, and are defined over different time horizons. Stulz (2010) in addition shows that CDS-contracts are generally traded over the counter instead of on public exchanges, so that data on these spreads are likely to be somewhat noisy.

Table 2 reports bivariate correlations between the variables included in the regression model, which have some convenient implications for our regression analysis. First, the upper two rows show that the average correlation between changes in a bank's value and changes in its default probability or CDS-spread is close to zero. This is due to the fact that default risk is predominantly driven by expected changes in banks' future market values rather than by changes in these current values, as is also implied by our default probabilities being calculated from future equity volatility. Due to this low correlation, collinearity between the common shock and contagion regressors in Equation (4) is unlikely to affect our coefficient estimates. Second, the next two rows show that the correlation between changes in default probabilities and between changes in CDS-spreads is low as well, so that collinearity between our default risk variables is unlikely to be an issue. Finally, the last row reports a somewhat surprising result, showing that changes in default probabilities and CDS-spreads on average are virtually uncorrelated. This finding suggests that they capture different aspects of default risk, so that we use each of them in our regression analysis as both measures are popular indicators of default risk in the literature.

Figure 1: Cross-sectional averages of market values, probabilities of default, and CDS-spreads



4 Empirical analysis

Table 3 reports the results from estimating Equation (4) using pooled ordinary least squares. To facilitate the interpretation of the coefficients, we divide each variable in the model by its standard deviation before estimating the regression, so that each coefficient directly indicates the regressor's correlation with the dependent variable. This transformation also avoids our coefficient estimates from being predominantly driven by the large banks in the sample, whose changes in market values would otherwise account for a large part of the variation in the dependent variable. By doing so we focus on the impact of contagion on the system of banks as a whole, rather than on a smaller subset thereof. To analyse the impact of contagion on such individual banks, we also estimated the regression using cross-section specific γ_{ij} coefficients, which yields similar outcomes as our analysis below.[6]

The first row in the upper panel reports the correlation and contagion coefficients for the full sample of 96 banks, calculated as the average of the estimates obtained for the 96 pooled regressions equations. The first statistic shows that correlation between banks' market values on average amounts to 0.33, which the second column shows is significantly higher than zero in 86 percent of the cases. The average of the correlation estimates that are significantly higher than zero is equal to 0.36, as is reported in the third column. Despite the heterogeneity of our sample, common shocks are thus important driving forces of individual banks' market values.

The next statistics in the first row of the panel show the magnitude of the contagion effect. Puzzlingly, the average coefficient estimate is equal to 0.02, implying a very small positive impact of increases in banks' default probabilities on other banks' market values. The sign of the effect is thus opposite to what would be predicted by the contagion hypothesis. The next two columns show that the contagion coefficient is estimated to be significantly lower than zero in only 13 percent of the pooled regressions, which is a rather small number since at the chosen significance level we would expect falsely significant results in already 5 percent of the cases. The next column shows that the average significant contagion effect is equal to -0.08, while the last columns in the table report the average adjusted R-squared and number of observations for the estimated regression equations.

These first results indicate that the average correlation effect is relatively large, while an average contagion effect is completely absent since the coeffi-

[6]In fact, the most important difference with estimating common coefficients $\gamma_{.j}$ is that the contagion coefficients now sometimes have implausibly extreme values, which we avoid by estimating common contagion coefficients across cross-sections.

Table 3: Results from pooled ordinary least squares regressions

Regression equation: $\Delta V_{i,t} = \alpha_{ij} + \beta_{ij}\Delta V_{j,t} + \gamma_{.j}\Delta PD_{j,t} + \delta_{ij}\Delta PD_{i,t} + \zeta_{ij}\Delta PD_{.,t} + \epsilon_{ij,t}$

Model with default probabilities	Common shocks affecting i and j			Contagion from j to i				
	β_{ij}	$P(t > 1.645)$	$\beta_{ij} \vert t > 1.645$	$\gamma_{.j}$	$P(t < -1.645)$	$\gamma_{.j} \vert t < -1.645$	$\bar{R}^2$	N
Full sample	0.33	0.86	0.36	0.02	0.13	-0.08	0.19	12060
Sub-samples based on location								
i from US, j from US	0.48	0.96	0.49	0.02	0.20	-0.12	0.26	2702
i from EU, j from US	0.27	0.80	0.30	0.01	0.12	-0.13	0.15	8453
i from EU, j from EU	0.35	0.88	0.37	0.02	0.10	-0.08	0.22	9294
i from US, j from EU	0.28	0.79	0.31	0.03	0.14	-0.18	0.12	3094
Sub-samples based on size								
i is large, j is large	0.45	0.98	0.45	0.00	0.04	-0.14	0.27	5993
i is small, j is large	0.31	0.87	0.34	0.02	0.09	-0.10	0.17	6101
i is small, j is small	0.25	0.74	0.29	0.02	0.19	-0.07	0.14	5930
i is large, j is small	0.31	0.85	0.33	0.03	0.13	-0.11	0.18	6095

Model with CDS-spreads	Common shocks affecting i and j			Contagion from j to i				
	β_{ij}	$P(t > 1.645)$	$\beta_{ij} \vert t > 1.645$	$\gamma_{.j}$	$P(t < -1.645)$	$\gamma_{.j} \vert t < -1.645$	$\bar{R}^2$	N
Full sample	0.35	0.88	0.38	0.06	0.06	-0.14	0.27	6668
Sub-samples based on location								
i from US, j from US	0.49	0.97	0.49	0.16	0.00	-	0.44	1309
i from EU, j from US	0.30	0.82	0.34	0.09	0.00	-	0.20	5065
i from EU, j from EU	0.38	0.92	0.40	0.02	0.07	-0.15	0.26	5237
i from US, j from EU	0.27	0.80	0.30	0.09	0.15	-0.17	0.32	1518
Sub-samples based on size								
i is large, j is large	0.41	0.95	0.42	0.05	0.02	-0.14	0.31	5262
i is small, j is large	0.29	0.80	0.34	0.01	0.08	-0.10	0.19	1592
i is small, j is small	0.25	0.72	0.30	0.08	0.08	-0.14	0.18	1329
i is large, j is small	0.30	0.81	0.33	0.10	0.08	-0.18	0.25	4767

Note: ‘large’ bank are those in the left column of Table 1, while small banks are those in the right column. All variables have been divided by their standard deviations before estimating the regression. T-values are calculated using White cross-section heteroscedasticity robust standard errors.

cient has the wrong sign. When we focus on the subset of regressions where we do find a significant correlation and contagion effect, this contagion effect is still almost five (i.e. 0.36/0.08) times smaller than the ordinary correlation between market value changes. This implies that the impact of a one standard deviation change in bank j's default probability on bank i's market value amounts to only twenty percent of the effect of a one standard deviation change in bank j's market value. As a one standard deviation change in both j's default probability and j's market value are about equally likely to occur, this finding confirms that contagion effects are much weaker driving forces behind banks' market value changes than common shocks are.

The next rows in the table focus on the average coefficient estimates for several sub-samples of banks. This exercise allows us to analyse in more detail whether correlation and contagion effects are equal across banks with different characteristics. The table first reports coefficient estimates for sub-samples based on location, distinguishing between banks situated in the US and the EU. As it turns out, correlation between banks is higher when they are both from the same region, equalling 0.48 for US banks and 0.35 for EU banks on average. This finding is in line with the economic intuition that banks active in the same geographic region are more likely to be affected by common shocks than banks operating at very different locations. The correlation between banks in the US is higher than correlation between banks in the EU, which illustrates that Europe is the more heterogeneous region of the two.

As argued by IMF (2009), banks that are more interconnected are more likely to suffer from contagion between each other when one of them goes bankrupt. To the extent that banks from the same region are likely to be more interconnected as well, we would thus expect contagion between them to be larger. The estimates for the contagion coefficient for these location-based sub-samples do not provide any evidence for such an effect, however. Neither the estimated contagion effect nor the significance thereof tends to be larger when banks are located in the same region. This finding, which is in contrast with our results for the correlation effect, further suggests that contagion had only a very limited impact on banks' market values.

The lower four rows in the panel focus on average coefficient estimates for sub-samples based on banks' size. We distinguish between the fifty percent larger banks in the sample, included in the left column of Table 1, and the fifty percent smaller banks included in the right column of the table. The results show that correlation between larger banks tends to be higher than correlation between smaller banks, which is in line with the intuition that larger (universal) banks tend to engage in the same type of activities, while smaller (specialised) banks tend to be more active in local niche markets.

Amongst others, IMF (2009) argues that especially the failure of large banks can be expected to have a contagious impact on other banks in the system, which in more popular terms is referred to as the too-big-to-fail hypothesis (although this effect can also refer to the impact of a large bank's default on the real economy). Somewhat surprisingly, the estimates for the contagion coefficient do not provide any evidence for such an effect: contagion from larger banks is not stronger or more often significant than contagion from smaller banks. The coefficient estimates for banks' default probabilities thus do not seem to pick up much of a contagion effect, which strengthens our finding that such effects are of only limited importance.

The rather small contagion effects in the upper panel of the figure could be due to our default probabilities being imperfect indicators of banks' default risk. For a sub-sample of 55 banks for which we have CDS-spreads available, we therefore use these as indicator of banks' default risk as well. The lower panel in the figure presents the results, which turn out to be highly similar to the ones for the regressions using default probabilities. For the sample as a whole the average correlation effect equals 0.35, which is significant in 88 percent of the regressions. The average contagion effect is again of the wrong sign and is significantly negative in only 6 percent of the cases, which at the chose significance level would be expected just by chance alone. As before, focusing on sub-samples of banks leads us to find variations in the correlation effect in line with economic intuition, while for the contagion effect we do not find such differences across sub-samples. In fact, significant contagion effects from US banks turn out to be absent altogether.

We have shown that markets expect the contagious impact from the default of an individual bank j to be fairly small, which holds for regressions with common as well as cross-section specific contagion coefficients, for regressions using default probabilities as well as CDS-spreads as indicators of bankruptcy risk, and for sub-samples based on banks' location as well as their size. We now also examine the impact of contagion from the combination of banks included in the regression equation. To this end, we compare the adjusted R-squared from the regression in Equation (4) with the adjusted R-squared from a regression where the $\Delta PD_{j,t}$ and $\Delta PD_{.,t}$ variables have been omitted. As it turns out, the average adjusted R-squared for the regressions without these contagion effects lies only about 0.03 points below the full-sample averages reported in Table 3. Although a standard F-test finds this difference to be statistically significant, from an economic perspective it is rather small, which confirms that contagion effects account for only a small part of the observed changes in banks' market values.[7]

4.1 Contagion from Lehman Brothers

Our finding that expectations of interbank contagion explain only a very limited amount of banks' market value changes during the credit crisis seems to be at odds with the aftermath of the Lehman Brothers default on 15 September 2008. After this date, counterparty risk awareness spread through the financial system, with for instance quickly rising money market rates as the result. While it seems only natural to conclude that this turmoil was caused by the default of Lehman Brothers, Taylor (2009) and Huertas (2010) argue that it was triggered by markets' uncertainty about the ability of governments to bail-out troubled financial institutions. Such safety nets play a large role in market participants' risk assessments, as was made explicit when Moody's (2007) announced that its bank credit ratings would be made to reflect the likelihood of a government rescue operation in case of an imminent default. Consequently, Icelandic banks received a five-step upgrade to a triple-A rating, which until then had been reserved for only the most solvent of financial institutions. The (threat of) removal of government safety nets can thus have a substantial impact on the valuation of financial intermediaries and on the interest rates against which they can borrow funds (see also Gropp, Gründl, and Güttler 2010). Instead of being caused by contagion, the aftermath of the Lehman default could thus just as well be due to a common shock stemming from the withdrawal of the US government safety net.

Table 4 examines in more detail to what extent financial markets expected a potential default of Lehman Brothers to be contagious. The table reports the outcomes from running regressions as in Equation (4) while including Lehman Brothers as bank j. The results show that changes in Lehman's market value are especially correlated with changes in market values of other US or large banks, while on average the correlation equals 0.26 for the regressions using default probabilities and 0.30 for the regres-

[7] Omitting $\Delta PD_{i,t}$ from the regression as well causes the adjusted R-squared to decline by an additional 0.03 points for the regressions using default probabilities, and by an additional 0.09 points for the regressions using CDS-spreads. These declines in explanatory power can however not be fully attributed to any contagion effects, since for instance also an increase in risk aversion or a loss on bank i's investment portfolio would lower bank i's market value while increasing its CDS-spread. If one could properly account for these effects and for the explanatory power due to contagion coefficients with the wrong sign, the decline in the R-squared caused by omitting any contagion effects from the regression is probably fairly small.

sions using CDS-spreads. Interestingly, the coefficient for these default risk indicators is significantly negative in none of the regression equations, while it generally is of the wrong sign as well. These findings are in line with those reported in Table 3 for the sample as a whole.

5 Discussion and implications

Our empirical analysis shows that changes in market participants' valuation of banks are correlated with each other, but not with changes in their assessment of banks' default probabilities. While the combined effect of default probabilities increasing across banks contributes somewhat to explaining declines in banks' market values, this effect is rather small and cannot easily be traced to contagion from one or more individual banks in particular. Hence, when for instance Citigroup reports a large loss on its investment portfolio, market participants seem to be mainly interested in the information this provides about the performance of similar investments on other banks' balance sheets, and apparently care much less about the loss's impact on the probability that Citigroup goes bankrupt. This finding suggests that common shocks are the main drivers of simultaneous changes in banks' market values, while contagion is of only minor importance.

That market participants expect contagion to be of minor importance can be the result of their belief in the effectiveness of financial regulation. Supervisors after all aim to minimise contagion by imposing limits on large exposures to individual counterparties and to investments in a single asset class, as well as by requiring the posting of collateral to mitigate counterparty credit risk. Indeed, concerning the aftermath of the Lehman bankruptcy, BIS (2009, p.24) concludes that "Lehman-referencing CDS exposures turned out to be smaller than feared. They eventually translated into relatively modest net settlement payments of about USD 5.2 billion, which would be closed out without incident in late October." In addition, our findings might be due to market participants expecting governments to prevent the contagious fallout from any defaulting banks. If so this would be evidence of widespread moral hazard, but as discussed above such beliefs are unlikely to fully explain our results.

If financial markets' are correct in expecting that bank defaults do not have a contagious impact on the financial system, the simultaneous declines in banks' market values have been primarily due to common shocks affecting banks with similar exposures to the economic and political environment. Examples of such shocks are a decline in U.S. house prices, a global reces-

Table 4: Results from pooled ordinary least squares regressions for Lehman Brothers

Regression equation: $\Delta V_{i,t} = \alpha_{ij} + \beta_{ij}\Delta V_{j,t} + \gamma_{.j}\Delta PD_{j,t} + \delta_{ij}\Delta PD_{i,t} + \zeta_{ij}\Delta PD_{.,t} + \epsilon_{ij,t}$, where j refers to Lehman Brothers.

Model with default probabilities	Common shocks affecting i and j			Contagion from j to i				
	β_{ij}	$P(t > 1.645)$	$\beta_{ij}\|t > 1.645$	$\gamma_{.j}$	$P(t < -1.645)$	$\gamma_{.j}\|t < -1.645$	$\bar{R}^2$	N
Full sample	0.30	0.81	0.35	0.05	0.00	-	0.13	8226
Sub-samples based on location								
i from US	0.45	0.96	0.46	0.21	0.00	-	0.25	2125
i from EU	0.25	0.74	0.30	0.00	0.00	-	0.10	6101
Sub-samples based on size								
i is large	0.37	0.91	0.39	0.10	0.00	-	0.18	4050
i is small	0.23	0.69	0.29	0.00	0.00	-	0.10	4176

Model with CDS-spreads	Common shocks affecting i and j			Contagion from j to i				
	β_{ij}	$P(t > 1.645)$	$\beta_{ij}\|t > 1.645$	$\gamma_{.j}$	$P(t < -1.645)$	$\gamma_{.j}\|t < -1.645$	$\bar{R}^2$	N
Full sample	0.26	0.72	0.32	0.07	0.00	-	0.21	4667
Sub-samples based on location								
i from US	0.46	1.00	0.46	0.18	0.00	-	0.44	1006
i from EU	0.21	0.64	0.26	0.05	0.00	-	0.16	3661
Sub-samples based on size								
i is large	0.29	0.85	0.33	0.08	0.00	-	0.26	3477
i is small	0.17	0.36	0.26	0.04	0.00	-	0.10	1190

Note: 'large' bank are those in the left column of Table 1, while small banks are those in the right column. All variables have been divided by their standard deviations before estimating the regression. T-values are calculated using white cross-section heteroscedasticity robust standard errors.

sion, a change in monetary policy, or a change in governments' willingness to bailout troubled financial institutions. While financial market dynamics such as herding can amplify the impact of such shocks on the financial system, our results show that these shocks or the amplification thereof are not driven by changes in the default risk of individual banks. This finding is in line with the literature discussed in the introduction, which shows as well that common shocks rather than contagion are the main drivers of banking sector instability. If this is indeed the case, it has at least three implications for the current policy debate on financial regulation and financial crisis management.

First, financial supervision should have more attention for the risks stemming from similarities across banks' balance sheets, since this type of homogeneity is the main reason that large parts of the financial sector can simultaneously become unstable (see also Wagner 2010). Banks' exposure to these shocks is likely to increase over time due to continuous advances in global financial integration. These advances allow banks to increasingly invest in the same projects, either directly or indirectly through buying securitised assets, and might ultimately enable them to construct an optimal investment portfolio where idiosyncratic risk has been diversified away and only systematic risk remains (see Sharpe 1964). Under those circumstances, each shock will be a common shock by definition. Acharya and Yorulmazer (2007) show that banks also have a more perverse incentive to increase their exposure to common shocks, since regulators are more inclined to engage in bail outs when the number of failed banks is large (the too many to fail effect). From a social welfare perspective, it could be optimal when intermediaries avoid expose themselves to the same type of adverse shocks, and specialise in activities rather than diversifying across them. Reducing balance sheet similarities across banks might thus prove more effective then trying to identify 'systemically important' financial intermediaries.[8]

Second, the opacity of banks' balance sheets might have caused financial markets to erroneously interpret some adverse shocks to one or a few banks as a common shock to the system as a whole. Under asymmetric information investors will after all evaluate the value or riskiness of their own bank's assets using public signals about the asset quality of other banks. Effects such as these can lead to a classic lemon's market as described by Akerlof (1970), and are likely to have played an important role in the drying up of the market for securitised mortgage products. To reduce its vulnerability to

[8]In fact, this analysis once started as to identify such systemic banks using market data, but changed its focus when evidence for contagion was found to be largely absent.

such effects, each bank should provide transparency about the composition of its balance sheet, so that it increases its investors' knowledge about the quality of its assets and thus becomes less dependent on their confidence therein. Imposing objective accounting rules based on market valuation and full consolidation of so-called off-balance activities would be a natural first step. Paraphrasing Taleb (2009), increasing transparency would hopefully lead to an equilibrium where investors' 'confidence' is only relied upon by Ponzi-schemes.

Third, the use of government rescue operations to safeguard financial stability comes under question, since rescuing one bank not so much prevents contagion to other banks, but merely stabilises other banks by signalling that if needed they will receive a bailout as well. While during a crisis such rescue operations have a stabilising effect, their *ex ante* contribution to financial stability then becomes rather limited. Instead, if banks anticipate upon such bailouts in good times, the induced additional risk-taking renders the actual bailout nothing more than the transfer of a subsidy that was already factored into their business models and risk management policies. Such implicit guarantees then reduce market participants' regard for economic fundamentals, and sow the seeds of a future financial crisis.

6 Conclusion

Simultaneous defaults in the banking sector are often attributed to interbank contagion, but can also be due to common shocks affecting banks with similar balance sheets. We disentangle these two effects by examining whether financial markets expected bank defaults to be contagious during the 2007–2009 global financial crisis. Our identification strategy is based on the presumption that if financial markets expect one bank's default to cause other banks to suffer losses as well, as implied by the contagion hypothesis, an increase in this bank's default probability should lead to a decline in the other banks' stock market valuations. For a global sample of the one hundred largest banks, we thus test for contagion by regressing changes in banks' market values on changes in other banks' market values and default probabilities. While we find changes in market values to be correlated across banks, a change in one bank's default probability or CDS-spread hardly affects the market's valuation of any other banks in the sample. This finding suggests that contagion risk is of minor importance compared to the impact of common adverse shocks affecting the banking sector as a whole. We discuss the implications hereof for financial regulation and the use of government rescue operations to safeguard financial stability.

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Appendix

Crosbie and Bohn (2003) show that a bank's probability of default PD can be calculated as

$$PD = \mathcal{N}(-DD) = \mathcal{N}\left(-\frac{\ln(V_A/D) + \left(\mu - 0.5\sigma_A^2\right)T}{\sigma_A\sqrt{T}}\right), \tag{5}$$

where $\mathcal{N}(\cdot)$ denotes the standard normal cumulative probability distribution. The probability of default is thus a function of the distance to default DD, which indicates the expected number of standard deviations that the bank is away from the point where its asset value is insufficient to cover its liabilities at the time these become due. This distance is a function of the market value of the bank's assets V_A, the expected return on assets μ, the standard deviation thereof σ_A, the book value of debt D, and the maturity thereof T. To obtain the market value of assets, Crosbie and Bohn (2003) use the option pricing framework by Black and Scholes (1973) and Merton (1974), which links V_A to the market value of equity V as

$$V = V_A\mathcal{N}(d_1) - e^{-rT}D\mathcal{N}\left(d_1 - \sigma_A\sqrt{T}\right), \tag{6}$$

with $d_1 = \frac{\ln(V_A/D)+\left(r+0.5\sigma_A^2\right)T}{\sigma_A\sqrt{T}}$ and r being the risk-free interest rate. The standard deviation of expected future asset returns σ_A in turn can be related to the standard deviation of expected future equity returns σ via

$$\sigma = \frac{V_A}{V}\mathcal{N}(d_1)\,\sigma_A. \tag{7}$$

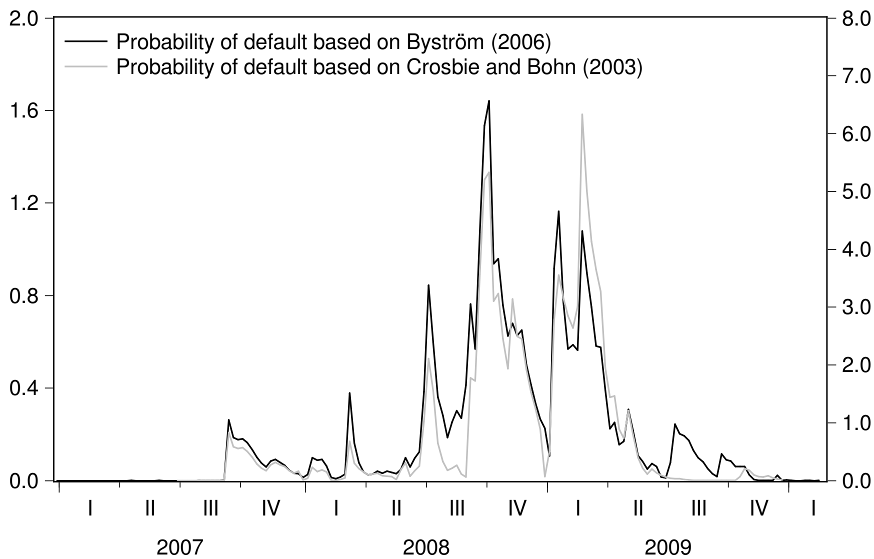
While it provides an internally consistent approach to derive the probability of default PD, solving the above system of Equations (5)-(7) requires data on D, T, r, and μ, which are notoriously difficult to obtain especially on a high-frequency basis (we cannot use ex-post statistics since market participants did not have these available when they engaged in the trading decisions leading to the observed values for V and σ). Book values of debt D can only be obtained for the year-end from banks' annual reports, and are generally not itemised to different maturities T. In practice, D is often estimated as the interpolated sum of ex-post data on short-term debt and fifty percent of long-term debt, while it is assumed that this full amount has a homogeneous maturity structure T of one year. Risk-free interest rates r only exist in theory and are often approximated by the return on U.S.

Treasury Bills, while expected future asset returns μ are constructed by extrapolating historical asset returns using a moving average of several months (see for instance Vassalou and Xing 2004, Duffie, Saita, and Wang 2007). These approximations seem quite crude, and are unlikely to reflect the actual beliefs of market participants regarding for instance the risk-free interest rate during crisis interventions by the Federal Reserve, or the debt maturity structure and future asset returns of Lehman Brothers' just before this institution went bankrupt.

In light of these data limitations, we follow Byström (2006) and use only stock market data to calculate the distance to default as $DD = 1/\sigma$. We estimate σ as the forecast from a GARCH model fitted to the time series with logarithmic equity returns. Byström (2006) finds that this measure is equal to the distance to default implied by CreditGrades, a structural model to calculate credit spreads that was introduced by the risk management firm RiskMetrics in 2002, and was endorsed by Deutsche Bank, Goldman Sachs, and JP Morgan. Moreover, he shows that especially for highly levered firms such as banks, $1/\sigma$ closely approximates the distance to default in Equation (5). As our approximation thus has the same $z-$score functional form as the original distance to default, which Bharath and Shumway (2008) show is the main driving force behind this measure's ability to forecast actual bankruptcies, we can map it to the standard normal distribution to obtain the default probability PD. Figure 2 shows that the resulting probabilities of default are similar to the ones implied by Equation (5).[9]

[9] We calculate the Merton (1974) distance to default using the same approach as Vassalou and Xing (2004) and Duffie, Saita, and Wang (2007), setting D equal to short-term debt and fifty percent of long-term debt (obtained from Datastream and interpolated to a weekly frequency), setting r equal to the return on U.S. Treasury Bills obtained from the Federal Reserve Board, and calculating μ as the six-month moving average of logarithmic asset returns. For equity volatility σ we use the GARCH estimates discussed above.

Figure 2: Cross-sectional averages of probabilities of default based on Byström (2006) and on Crosbie and Bohn (2003)



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