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Systemic Risk and Bank Size

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Systemic Risk and Bank Size

Abstract

In this paper we analyse aggregate and firm level systemic risk for US and European banks from 2004 to 2012. We observe that common systemic risk indicators are primarily driven by firm size which implies an overriding concern for "too-big-to-fail" institutions. However, smaller banks may still pose considerable systemic threats, as exemplified by the Northern Rock debacle in 2007. By introducing a simple standardisation, we obtain a new risk measure that identifies Northern Rock as a top ranking systemic institution up to 4 quarters before its bailout. The new indicator also appears to have a superior ability to predict which banks would be affected by the most severe stock price contractions during the 2007-2009 sub-prime crisis. In addition we find that a bank's balance sheet characteristics can help to forecast its systemic importance and, as a result, may be useful early warning indicators. Interestingly, the systemic risk of US and European banks appears to be driven by different factors.

Keywords

systemic risk, financial crisis, bank regulation, contingent claim analysis

JEL Classifications

G01, G21, G28

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1 Introduction

As a result of the sub-prime crisis of 2007-2009 and the unfolding sovereign debt crisis, systemic risk in the finance industry has become a hot topic in academic and policy circles. This is because of the substantial damage a financial crisis may cause to the real economy (see, for example, Caprio and Klingebiel, 1996 and Hoggarth et al., 2002) and the fact that financial institutions do not internalize the costs of such negative externality. As a consequence, addressing systemic risk is at the heart of new financial regulation such as the Dodd-Frank Act in the US and the new Basel III agreement. A capital surcharge is required by Basel III on domestic and global systemically important banks (see Basel Committee on Banking Supervision, 2012 and 2013). On the other hand, the Dodd-Frank Act explicitly emphasizes the need to provide enhanced regulation of firms and sectors that pose systemic risk (see Richardson, 2011). A Pigouvian tax has also been proposed to force systemically important financial institutions (SIFIs) to internalise the costs of crises and thus reduce their severity (see Morris and Shin, 2008 and Acharya, Pedersen, Philippon and Richardson, 2011). However, any solution to the problem of systemic instability relies, as a first step, on measuring systemic risk and identifying SIFIs.

This paper contributes to the existing literature in four ways. First, although large banks are commonly considered of systemic importance and firm size is typically an important driver of systemic risk measures (see, for instance, De Jonghe, 2010, Hovakimian, Kane and Laeven, 2012 and Huang et al 2012b), there is growing evidence that size may not be a persistent determinant of systemic risk in past crises (Weib et al 2014), nor be a prominent contagion factors among large international banks (Lopez-Espinosa et al 2012 and 2013). We propose a standardised systemic risk indicator that enables us to control for the overshadowing effect of firm size and bring forth other factors that contribute to the systemic importance of an institution, namely interconnectedness and default risk. We find that the new measure allows us to single out Northern Rock, a relatively small bank which proved to have high contagion potential, as a top ranking systemic institution consistently over the 4 quarters before its bailout. This is remarkable considering that UK's Financial Services Authority stated that the bank "is solvent, exceeds its regulatory capital requirement, and has a good quality loan book" days before its demise.[1] The new standardised indicator also appears to be better than the size-polluted (non-standardised) one at identifying banks that suffered the largest stock depreciation during the subprime crisis. We conclude that standardised and non-standardised measures complement one another and should both be considered by financial regulators.

[1] See Hull (2010) p. 392.

Second, we put forward a new indicator of banking system fragility (BFI) as the average percentage default barrier in the system. We recognise that different systemic risk indicators do not necessarily give consistent messages, as pointed out by Giglio et al (2013). For example, alternative indicators may peak at different points in time that correspond to different phases of the same crisis or different types of crises. Our banking fragility indicator aims to improve on previous systemic risk measures by taking into account the "effective" level of short term indebtedness of the banking sector as perceived by the equity market. Effective short term debt, which is the one most likely to push an institution into default if not repaid or rolled over, may change considerably over time although its balance sheet value may remain virtually unaltered. In normal market conditions the effective level of short term debt may be close to zero because short term liabilities can be easily rolled over. In a crisis, a roll over may not be possible (see Acharya, Gale and Yorulmazer, 2011) thus increasing the bank's exposure to refinancing risk and, as a result, default risk. Our default barrier indicator naturally accounts for short term wholesale funding risk, which has been shown to be a key systemic factor (Lopez-Espinosa et al 2012). But, by reflecting the market perception of short term liabilities, it also encompasses retail funding risk (i.e. deposit withdrawal) which exposes banks to "runs" (e.g. see Goedde-Menke et al 2014), and changes in "effective" maturity resulting from the varying degree to which the bank can rollover its debts under different market conditions.

Our third contribution is a new measure of systemic risk for individual banks. Our measure is conceptually similar to the one used by Brownlees and Engle (2011), Acharya, Engle and Richardson (2012) and by US and European regulators in their recent stress testing exercises across the banking sector.[2] However, we depart from the approaches used so far in that our indicator is based on the likelihood that banks satisfy a leverage cap as specified in the new Basel III regulation. The alternative of tying systemic risk to the likelihood of minimum capital requirements not being met is, in our opinion, potentially less reliable. This is because regulatory capital depends on risk weights whose effectiveness can be undermined through regulatory arbitrage (see, for example, Acharya and Schnabl, 2009).[3]

Our fourth contribution is an examination of whether the level of systemic risk posed by a bank can be predicted by the bank's fundamental value drivers such as size, leverage, assets liquidity

[2] See Acharya, Engle and Richardson (2012) for details.

[3] Acharya and Schnabl (2009) state that "... the Basel capital requirements were simply gamed by banks that had high ratios of total assets to risk-weighted assets. They were indeed much less safe than their capital requirements showed them to be, ended up holding less capital than was suitable for their true risk profile, and therefore suffered the most during the crisis".

and profitability. Our intent is to see whether such drivers could be employed to design effective regulation and government policies to curb systemic risk.

Our analysis shows that systemically important banks, identified by using our size-polluted measure, match closely those reported at the end of 2011 by the Financial Stability Board established by the G-20. Further, the extent of the bailouts in the Capital Purchase Program of the US government is significantly positively related to our measures of systemic risk 6 months before the capital injections. Further inspection reveals that the allocation of bailout funds was mainly driven by bank size and was unrelated to our standardised systemic risk indicator. This suggests that too-big-to-fail considerations may be the dominant factor in bailout decisions which, in future crises, could leave the financial system exposed to systemic risk stemming from smaller, but highly contagious, institutions.

We also find that the overall systemic risk in the financial system, measured as the likelihood that the asset value of banks in distress is above a given threshold, peaked in March 2009 in the US as well as Europe, as the stock market reached its lowest point. However, with our new indicator of bank fragility (BFI), the US and Europe behave rather differently. The results suggest that funding risk, as captured by the BFI index, has a more regional connotation and was highest in the country/region when the crisis originated, i.e. in the US, during the sub-prime crisis and in Europe during the sovereign debt crisis. The finding also implies that funding risk is not necessarily the same as systemic risk as both risks are influenced differently by the corrective policies implemented by governments and central banks in the turmoil periods (availability of emergency central bank funding, government sponsored bail outs, capital injections and so on).

Finally, when trying to predict an individual bank's contribution to systemic risk with lagged balance sheet characteristics we find that it is positively related to size and leverage and negatively related to tier 1 capital and profitability. These results support the stance taken by regulators in Basel III who have introduced a new leverage constraint and higher tier 1 capital for systemically important banks.

The rest of the paper is organized as follows. Section 2 summarises the existing literature. Section 3 describes the methodology and the model. Section 4 introduces the sample and data sources. Section 5 presents our empirical results and Section 6 concludes.

2 Literature review

A variety of systemic risk measures has been proposed since the start of the sub-prime crisis. Bisias et al (2012) provide a comprehensive summary, and emphasise that there is no single "pressure gauge" that can fully detect crises. Indeed, Hansen (2013) warns that model misspecification can be a serious challenge when trying to devise systemic risk measures. One approach is to focus on contagion effects, largely relying on detailed bank-specific information, such as the level of banks' mutual exposures. As a result, network analysis has been developed to model interbank lending and contagion effects (Chan-Lau, Espinosa and Sole, 2009, the International Monetary Fund 2009 and Martinez-Jaramillo et al., 2010).[4] Taking into account feedback effects, a network based structural model is also adopted by Gauthier, Lehar and Souissi (2012) to examine the impact of macro-prudential capital requirements on systemic risk. Stress tests conducted by regulators and Duffie's (2011) "10-by-10-by-10" policy proposal also exploit detailed data on the exposures of individual financial firms.

Another approach is to look at bank asset co-movements and relies on publicly available market data. Along this line, the CoVaR put forward by Adrian and Brunnermeier (2008) uses quantile regressions to measure the increased Value-at-Risk (VaR) of the financial system when a specific financial firm is in distress. Girardi and Ergun (2013) generalize the original CoVaR by extending the definition of financial distress to include more severe events than in the original measure. Lopez-Espinosa et al. (2012 and 2013) observe that short-term wholesale funding (funding instability) is the main determinant of CoVaR in recent crises. Although popular due to its simplicity, the CoVaR measure is often criticized because it does not explicitly take into consideration a systemic institution's capital structure.

Brownlees and Engle (2011) and Acharya, Engle and Richardson (2012) propose a new systemic risk indicator (hereafter AER) that captures a financial institution's contribution to the total capital shortfall of the financial system. This contrasts with the structural model approach in Lehar (2005) which is also adopted in our work. Through a structural model one can explicitly define a crisis as the joint default of a group of institutions. In Acharya et al (2012), a crisis event is defined as a 40% decline in the 6-month cumulative return of a stock market index. However, not all large stock price corrections may trigger collective defaults.[5] For instance, the burst of the

[4] See also Boss et al. (2004), Muller (2006) and Nier et al. (2006).

[5] While our definition of a financial crisis is also sensitive to negative stock market returns, a big drop in the market index is in itself not enough to trigger a systemic crisis. In our model, unlike in Acharya et al (2012) the vulnerability of the banking system (e.g. average leverage) is also important. It is conceivable that banks may not default even after a severe stock market contraction if their leverage is low. On the

internet bubble in the early 2000s led to a stock market contraction of about 50% from peak to trough (for S&P500 as well as FTSE100) but without the systemic implications seen during the Great Recession following the sub-prime crisis. In this sense, the crisis condition used by Acharya et al (2012) is more “systematic”, while the structural model approach is more “systemic”.

Closely related is the methodology proposed by Banulescu and Dumitrescu (2014) who measure systemic risk in a fashion inspired by the component Value-at-Risk concept. Principal component analysis and Granger-causality tests have also been utilized to measure the degree of commonality and interconnection in a group of financial firms and hence their implied systemic risk (Kritzman et al., 2011 and Billio et al., 2012). Further contributions in this area include Lehar (2005), Gray, Merton and Bodie (2007), Gray and Jobst (2010), Suh (2012), and Saldias (2013) who adopt contingent claim analysis to identify systemically important banks.

Huang, Zhou and Zhu (2009, 2012a and 2012b) and Black et al. (2013) measure the systemic risk of the banking sector as a hypothetical distress insurance premium estimated from credit default swap prices. Comparing several systemic risk measures, Rodriguez-Moreno and Pena (2013) confirm that CDS prices are more informative than interbank rates or stock market prices.

Recent additions to the fast growing literature in this area are Patro, Qi and Sun (2013) who find that systemic risk is related to the level of correlation among the idiosyncratic components of financial institutions’ stock returns, and research that aims at predicting systemic events or developing early warning indicators (see Lo Duca and Peltonen, 2013, Hautsch, Schaumburg and Schienle, 2014, Jobst, 2013 and Oet et al., 2013).

Our paper is closely related to the literature that examines the balance sheet determinants of a bank’s systemic risk. Hovakimian, Kane and Laeven (2012) find that, for US banks, size, leverage, and asset risk are key drivers of systemic risk. In contrast, Weiß, Bostandzic and Neumann (2014) conclude that no bank characteristics are persistent determinants of systemic risk across a number of past financial crises. Instead, the authors argue that global systemic risk is driven by the regulatory environment and deposit insurance schemes. De Jonghe (2010) documents that a bank’s systemic risk increases with the importance of non-traditional banking activities as measured by non-interest income and particularly trading income. In a more recent study, Brunnermeier, Dong and Palia (2012) confirm the destabilizing effect of banks’ non-traditional

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other hand, a milder erosion of market value might have systemic consequences in a high leverage scenario.

activities. However, they find no difference between trading income and other non-interest income with respect to systemic risk.

Other factors that have been found to have good explanatory power for systemic risk are the level of bank competition, with higher competition causing the risk of contagion to fall (Anginer, Demirguc-Kunt and Zhu, 2014) and the extent of securitisation activity (Battaglia and Gallo, 2013).

3 Methodology

In order to measure systemic risk for the whole financial system and at the bank level, we define a bank in distress as the event that occurs when the bank's assets fall below the bank's debt at a future time t. The actual market value of total assets of a financial firm $A_{i,t}$ is not observable in that a bank's portfolio is composed of both traded securities and non-traded assets. As a result, we model equity as contingent claims (a call option) on the assets and back out the asset value accordingly. Debt $D_{i,t}$, our "effective" level of short term indebtedness which represents the default trigger for bank *i*, is also difficult to determine due to the complexity and opaqueness of a bank's balance sheet, as pointed out, for example, by Crosbie and Bohn (2003). To quantify $D_{i,t}$, we need to take into account short-term debt and part of long-term debt as suggested by Moody's KMV and Vassalou and Xing (2004).[6] However, instead of choosing a somewhat arbitrary portion of long-term debt to determine the default trigger (it is 50% in the Moody's KMV model), we assume, similarly to Suh (2012), that the $D_{i,t}$ is a portion of total liabilities $L_{i,t}$, namely $D_{i,t} = \delta_{i,t}L_{i,t}$. Note that, unlike in Suh's paper, $\delta_{i,t}$, our percentage "default barrier", is time-varying because we intend to capture the changing market perception of the barrier over time. We define our new banking sector fragility indicator (BFI) as the average $\delta_{i,t}$ across all banks,

$$\mathrm{BFI_t} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \delta_{i,t}}{\mathrm{n}} \tag{1}$$

where n is the number of banks in the system.[7]

[6] Vassalou and Xing (2004) state: "It is important to include long term debt in our calculations for two reasons. First, firms need to service their long-term debt, and these interest payments are part of their short term liabilities. Second, the size of long term debt affects the ability of a firm to roll over its short-term debt, and therefore reduce its risk of default."

[7] We have also looked at an average delta weighted by the assets of each bank and results are qualitatively unchanged.

Assuming that the asset value of a bank follows a Geometric Brownian Motion (GBM), under the risk-neutral measure, the bank's equity $E_{i,t}$ can be seen as a call option on the bank's assets with a strike price equal to debt with maturity at T ($D_{i,T}$). Following Lehar (2005), we assume $D_{i,t}$ grows at the risk free rate r_f, that is $D_{i,T}=e^{r_f(T-t)}D_{i,t}$. Therefore, the risk-free rate discount factor cancels out in the call option pricing equation, which becomes:

$$E_{i,t} = A_{i,t}N(d_{1t}) - D_{i,t}N(d_{2t}) \tag{2}$$

with

$$d_{1t} = \frac{\ln(A_{i,t}/D_{i,t}) + \left(\frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_{2t=}d_{1t} - \sigma\sqrt{T}$$

where σ is the asset return volatility, T is assumed to be 1 year, following the convention, and N(·) is the cumulative standard normal density function. We apply the maximum likelihood estimator proposed by Duan (1994) and Duan (2000)[8] to estimate the parameters of interest:

$$L(E,\mu,\sigma,\delta) = -\frac{m-1}{2}\ln(2\pi) - (m-1)\ln(\sigma) \\ -\sum_{t=2}^{m} ln\tilde{A}_t - \sum_{t=2}^{m}\ln\left(N(\tilde{d}_{1t})\right) - \frac{1}{2\sigma^2}\sum_{t=2}^{m}\left[\ln\left(\frac{\tilde{A}_t}{\tilde{A}_{t-1}}\right) - \mu\right]^2 \tag{3}$$

where m is the number of observations and μ is the expected asset return. The estimation of μ, σ, δ and A_t follows an iterative procedure. First, σ and δ are given an initial value. Then, estimates of A_t and d_{1t} ($\tilde{A}_t$and $\tilde{d}_{1t}$) are implied from equation (2). Next, parameters μ, σ and δ are obtained by maximising the likelihood function in equation (3). Following this, the estimated

[8] We thank Jin-Chuan Duan and Tao Wang for sharing their Matlab code.

σ and δ are used as new initial values. Iterations stop when the increase in the value of the likelihood function or the change of parameters is smaller than 1e-8.

For each bank in our sample, the monthly time series of total assets $A_t$and the corresponding parameters of the process σ, μ and δ are estimated, using a rolling window of the previous twenty-four months, as in Lehar (2005).

After the time series of total assets has been derived, we measure time-varying asset volatilities and correlations through the well-known EWMA model:

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\ln\left(\frac{A_{i,t}}{A_{i,t-1}}\right)\ln\left(\frac{A_{j,t}}{A_{j,t-1}}\right) \tag{4}$$

where $\sigma_{ij,t}$ is the covariance between asset returns of bank i and j at time t. Following the RiskMetrics framework developed by J.P. Morgan, the decay factor λ is set equal to 0.94.

For each month in the sample period, a variance-covariance matrix (Σ_t) can be estimated using Equation (4). The matrix will be employed in Monte Carlo simulations to take into account banks' "interconnectedness" when calculating overall systemic risk in the industry and the systemic risk contribution of individual banks. Following Lehar (2005), we define overall systemic risk as the probability of a crisis event which occurs when the proportion of the assets of distressed banks to the total assets of all banks exceeds a certain threshold θ (e.g. θ =10%) over the next six months:[9]

$$Overall\ systemic\ risk_t = Prob[Crisis]$$

$$= Prob[\textstyle\sum_{\boldsymbol{i}}(A_{i,t+1}\,|A_{i,t+1} < \delta_{i,t}L_{i,t+1}) > \theta \textstyle\sum_{\boldsymbol{i}} A_{i,t+1}] \tag{5}$$

where we assume that $L_{i,t+1} = L_{i,t}$.[10]

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[9] An overall systemic risk index can also be calculated in terms of the number of banks in distress, see Lehar (2005) and Suh (2012).

[10] To derive (2) we assume that a bank's debt grows at the risk free rate. However, this assumption implies that in (2) a risk free rate does not need to be specified as it cancels out in the pricing equation. In equation (5), on the other hand, an explicit growth rate for liabilities needs to be spelt out in order to derive $L_{i,t+1}$. Given that interest rates during the crisis were very low, combined with the difficulty of identifying a "riskless" rate during the sub-period of the sovereign debt crisis, for simplicity we assume that the risk free rate is zero.

We derive the systemic risk contribution of a bank, SYR, as the bank's expected capital shortfall during a crisis:

$$SYR_{i,t} = E[(kA_{i,t+1} - Equity_{i,t+1}) \,|Crisis] \tag{6}$$

where k is the minimum leverage, measured as an equity-to-asset ratio, which is set in Basel III at 3% of total assets. $kA_{i,t+1}$ then represents a non-risk based minimum capital requirement. According to the new Basel regulation such a requirement appears to be a necessary complement to risk based capital measures because it is less subject to manipulation by banks and not influenced by inherent problems in regulatory risk weights.[11]

A relative measure of $SYR_{i,t}$ that takes into account the systemic importance of a bank in relation to the systemic risk in the financial system can be easily calculated as:

$$rSYR_{i,t} = \frac{SYR_{i,t}}{\sum_i \left(SYR_{i,t} \mid SYR_{i,t} > 0\right)} \tag{7}$$

As we find that firm size is often a dominant contributing factor in our systemic risk measures, which can overshadow other factors (e.g. leverage and interconnectedness) we also employ a standardized systemic risk contribution, which is simply a bank's systemic risk contribution $SYR_{i,t}$ divided by its total assets:

$$sSYR_{i,t} = \frac{SYR_{i,t}}{Total\ Assets_{i,t}} \tag{8}$$

In order to compute the above systemic risk variables, at each point in time in the sample period, Monte Carlo simulations are used to generate future scenarios of bank-specific asset values. In each scenario, the multivariate distribution of predicted asset values at a given future horizon

[11] For example, the internal rating based approach in Basel II uses risk weights that are based on several assumptions (e.g. single risk factor model, well diversified portfolio, ...) which may not be appropriate for all banks across all portfolios.

(e.g. in 6 months) is obtained by using the Cholesky-decomposition of the variance-covariance matrix (Σ_t) estimated with the EWMA model. So, a scenario s at time t+1 is generated as:

$$A_{i,t+1}^{s} = A_{i,t} \exp\left(\mu_{i,t}T + \mathrm{Chol}(\Sigma_t)^T \varepsilon_t \sqrt{T} - \frac{1}{2}\sigma_{ii}^2 T\right) \tag{9}$$

where $\mathrm{Chol}(\Sigma_t)$ is an upper triangular matrix so that $\Sigma_t = \mathrm{Chol}(\Sigma_t)^T \mathrm{Chol}(\Sigma_t)$ and ε_t is a standard normal random variable. We simulate $A_{i,t+1}^{s}$ for 100,000 scenarios simultaneously for all banks, each month in the sample period.

4 Data

We study the largest 50 US banks and the largest 45 European banks in Bloomberg (in terms of total assets as of the end of June 2007) for which equity prices and total liabilities are available from December 2001. We include dead banks to address survivorship bias. For both US and European banks, equity prices are collected monthly and balance sheet data is collected quarterly from December 2001 until December 2012. Our sample of European banks covers all Euro area countries which joined the Eurozone before 2002. We add three more countries with large systemically important banks: Switzerland, Sweden and the United Kingdom.[12]

5 Empirical findings

We first apply the methodology explained in Section 3 to measure the magnitude of overall systemic risk in the banking sector. Then, we compute our new indicator of banking system fragility. Further, we derive the contributions of individual banks to systemic risk in order to identify systemically important banks (SIFIs) with and without firm size standardisation. Lastly, we use a fixed effects panel regression to illustrate how a bank's characteristics can help us to predict its systemic importance after controlling for size effects.

5.1 Aggregate systemic risk and banking fragility indicator

A systemic event occurs when the proportion of the assets of distressed banks to the total assets of all banks exceeds a threshold θ within a predetermined time horizon τ. This corresponds to a

[12] Our sample includes the majority of countries covered by the stress tests conducted by the European Banking Authority (EBA) in 2011.

situation when normal banking intermediation is severely disrupted and credit supply is reduced to the extent that the real economy is adversely affected. In line with the previous literature (Lehar, 2005 and Suh, 2012), we choose θ=10% and τ=0.5 years.[13] Our banking sector-wide systemic risk measure is the probability of having such a systemic event.

Figure 1 shows the time series of overall systemic risk from December 2003 until December 2012 for both the US and the European banking systems. It is clear that the highest systemic risk with the longest duration occurred during the sub-prime crisis of 2007-2009, in both regions. As one would expect, our systemic risk indicators increase sharply at the time of critical events, such as the Bear Sterns bailout (March 2008), the Lehman Brothers failure (September 2008), the stock market bottom (March 2009) and European sovereign debt hot spots (e.g. May 2010 and Summer 2011). Systemic risk in the US decreases much earlier and faster than in Europe after they both peak in March 2009.

Our banking fragility indicator BFI, which is the average default barrier across all banks in our regional samples, increases with the perceived level of short-term liabilities in the banking industry. In a crisis, short term debt could go up as liabilities that become due may become difficult to roll over. On the other hand, when the market perception of the implicit guarantee from the government gets stronger or emergency funding is made available by central banks, the BFI becomes smaller. Figure 2 shows the time series of the BFI for the US and Europe. Overall, the European banking system appears to be less fragile than its US counterpart throughout the sample period. In the US, the BFI was at its highest level during the sub-prime crisis, with a peak around the failure of Lehman Brothers in September 2008. However, in Europe, the BFI is largest around the time Greece accepted the first bailout in May 2010.

In the Summer of 2011 the fear of contagion in the Eurozone deepened following rumours of a Greek default and exit from the Eurozone. As shown in Figure 1, overall systemic risk in 2011 increases again for both the US and Europe. But, the BFI behaves differently in the two regions. In Europe, it continues to decrease, probably thanks to liquidity facilities provided to the banking sector following the establishment of the European Financial Stability Facility (EFSF) and the European Financial Stabilisation Mechanism (EFSM) in May 2010. By contrast, in the US, the BFI starts to increase again from July 2011. This may reflect the response of the market to new financial regulation. At that time, the Dodd-Frank Act had been in place for one year. The Act aims to dampen the “too big to fail” problem by various methods, such as the creation of an orderly liquidation authority and restrictions on the power of the Federal Reserve to save

[13] As a robustness check, we derive overall and bank specific systemic risk measures with equal to 5% and 20%, instead of the 10% used for our reported results. We do not find significant changes in our findings.

troubled banks. The implementation of these regulations raised concerns in the market about the ability of the financial watchdogs to act promptly to rectify new crisis scenarios (see Acharya et al, 2011)

Figures 3 and 4 show the dispersion of bank specific default barriers $\delta_{i,t}$, summarized in the BFI, for the US and the European banking systems, respectively, over the sample period. The distance between the 25% and 75% quantiles of the barriers increases dramatically during the financial crisis, indicating a sharp rise in perceived funding problems at weaker banks.

5.2 Standardised and non-standardised systemic risk indicators

To regulate SIFIs effectively and make them internalize bailout costs, it is essential to identify SIFIs and monitor how their systemic importance changes over time. In Table 1 we report a ranking of US (Panel A) and European banks (Panel B) by their systemic importance measured with our relative (non-standardised) and standardised indicators, rSYR and sSYR, and AER[14] at the end of 2007 and 2011. We also show the (unranked) list of SIFIs released by the Financial Stability Board (FSB)[15] in November 2011. If we look at the US (European) banks, it is interesting to note that the ranking based on our rSYR shares 12 out of 15 (15 out of 15) top risky banks with the AER measure in 2007 and 13 out of 15 (15 out of 15) in 2011. Also the 5 (14) systemically important banks released by the FSB are within the top 6 (17) in our 2011 ranking. The consistency of our results with alternative indicators suggests that, rather reassuringly, banks that can generate the most serious knock-on effects in the industry should not be difficult to identify and hence to regulate. Further, our rSYR-based 2007 US ranking reveals that 9 months before the Lehman Brothers failure, the top 15 risky banks include institutions that later either defaulted and/or were acquired following large losses (Wachovia, Washington Mutual, National City, Sovereign Bancorp) or received the largest capital injections from the US Treasury's Capital Purchase Program.[16,17] Although it was branded as a "Healthy Bank Program", the amount of money allocated to each bank may be taken as an indicator of the systemic importance of the bank from the government's perspective. Figure 5 shows the strong positive relationship between government capital injections and the rSYR measured 6 month before. This is also

[14] AER measures are available at vlab.stern.nyu.edu .
[15] The Financial Stability Board (FSB) is an international body that monitors and makes recommendations about the global financial system. It was established after the G-20 London summit in April 2009 as a successor to the Financial Stability Forum.
[16] 11 of the top 15 most systemically important banks (ranked with our rSYR measure) as of December 2007 are among the top 12 in the US Treasury's Capital Purchase Program in terms of amount received.
[17] The Troubled Asset Relief Program is a program of the United States government to purchase assets and equity from financial institutions to strengthen its financial sector that was signed into law on October 3, 2008. It was one of the government's measures in 2008 to address the subprime mortgage crisis.

confirmed by the significantly positive coefficient of rSYR in the regression results reported in Table 2 (model 1).

Even a casual look at the rankings produced by our and alterative systemic risk measures would reveal that the institutions that are found to pose the most serious systemic threats are also the largest ones. Figures 6 and 7 illustrate the distribution of systemic risk contributions for our US and European bank samples over time. The proportion of banks with non-trivial systemic importance is larger in Europe than in the US, which results in a distribution less skewed and less fat tailed in Europe as can be inferred from the higher 60% quantile ticks. This is not surprising as the US market is more concentrated than the European one with few very large institutions with an international presence followed by considerably smaller regional banks. This said, Europe too is characterised by several mammoth banks, which are considerably systemic. Indeed, as it can be seen from Table 1 there are 18 European banks with more than half a trillion dollar in assets as of 31 December 2007, relative to only 5 in the US.

Clearly, the larger a bank the more disruption it may cause if it fails. However, it is important to know if size is the only factor regulators take into account when devising their bailout programs. If so, this may be a cause for concern in that Northern Rock was not a large bank, relatively speaking. But it posed a major systemic threat. In this sense, a bailout program may be biased if prominently based on size as to obscure other important systemic factors, such as default risk and inter-connectedness which are reflected in our relative systemic risk measure (rSYR). Indeed, Figure 8 reveals that bailout funds distributed through the US Capital Purchase Programme are strongly related to bank size. To address this issue, in our regression analysis in Table 2 we also control for bank size separately in order to see if rSYR is still significant (model 2). It turns out that it is not, which suggests that the non-size systemic factors reflected in rSYR were not accounted for in the US government rescue program.

However, it is to be expected that large banks receive larger injections, even though, the size of the bailout may not reflect the “level of support” received by the bank. If a bank is 10 times bigger than another, it should receive an injection 10 times bigger in order to have the same “level of support” as the smaller one. On the other hand, if the injection is only 5 times bigger, then the smaller bank will have obtained double the level of support of the bigger one. To determine whether the level of support is related to our non-size related systemic risk factors, we regress relative rescue packages, where injection funds are divided by the asset size of the recipient bank, on our standardised systemic risk measure sSYR (Table 2, models 3 and 4). Again, the relationship is not statistically significant, as also illustrated in Figure 9. However, it now appears that, plausibly, the level of support declines as tier 1 capital increases. On the other hand, it increases with excessively negative or excessively positive asset growth, both of which may indicate or lead to a potential imbalance within the bank.

The next question is whether sSYR may capture important systemic related information not adequately conveyed by the unstandardized rSYR. To answer this question we look at the ability of the two measures to predict high distress levels, which are directly linked to default risk, a key indicator of systemic relevance. In Table 3 we report pre-crisis systemic risk rankings for the European and US banks with the largest drop in stock price during the following sub-prime crisis. We also add those institutions that were delisted due to default, nationalisation or merger. Our findings reveal that the rankings based on sSYR signal, on average, higher systemic risk than those based on rSYR, in both regions. Although by looking at individual cases the dominance of sSYR over rSYR is only marginal (60% and 53% of the cases in Europe and the US respectively), it turns out that the gap between the rankings from the two measures is largest when sSYR dominates. In other words, when the standardized measure is better, it is so by a greater margin (9.2 and 20.9 ranking positions for Europe and the US) than when the unstandardized measure dominates (4.5 and 7.3 respectively). Our conclusion is that sSYR does convey useful additional information over and above that which can be inferred from rSYR. The implication is that both measures should be looked at when assessing the systemic risk of individual banks. An interesting case study that supports the value of sSYR is Northern Rock. The bank that witnessed the first run in the UK for 150 years and was bailed out to prevent likely knock-on effects in the rest of the banking sector was consistently ranked within the top three systemic institutions by sSYR up to 2006Q3, 4 quarters before its bailout (see Figure 10).[18] This highlights the ability of the standardised indicator to pick up systemically important institutions despite their relatively smaller size.

5.3 Systemic risk precursors

One of the criticisms of systemic risk measures based on stock market data, like the ones employed in this study, is that they may signal a build-up in systemic risk at the aggregate level or for a specific bank, but only after it has already taken place. This would reduce the usefulness of such measure as regulatory tools though they would still be informative as they would enable policy makers to determine the extent of the risk in the system (for instance in relation to previous crises) and the threat posed by individual institutions. However, regulators need to identify systemic banks before they become a threat for the financial system. Indeed, the new

[18] The rankings for 2006Q4 and 2007Q1 are not available as the probability of a systemic event at those times was zero according to the overall systemic risk measure defined in equation (5).

Basel III rules state that banks that could cause systemic crises should be required to hold additional capital reserves to decrease the likelihood of such crises. Then, the identification of precursors that can help to explain our systemic risk indicators with some lead time would be useful tools that could provide valuable early warnings to regulators and government authorities. Moreover, their usefulness would be enhanced, if such precursors were based on easy-to-source publicly available data. With this in mind, we test whether lagged bank characteristics can explain our systemic risk measures. Table 4 contains summary statistics of our regression variables and their pairwise correlations for the US (Panel A) and Europe (Panel B). With the purpose of analysing the drivers of cross-sectional heterogeneity in banks' systemic risk (as shown in Figure 6 and Figure 7), we employ several explanatory variables: bank size measured as logarithm of total assets, total assets growth rate, return on assets as a measure of profitability, Tier1 capital ratio, leverage, liquidity computed as short-term assets over total assets as in Brownlees (2011) and deposit ratio computed as percentage of total assets. Data availability forces us to use a restricted sample period from Q1 2004 to Q4 2012. Following Brunnermeier, Dong and Palia (2012), quarterly fixed-effects are included in our regressions. We are aware that the dependent variable (sSYR) comes from a first-stage estimation, which may introduce measurement error and, as a result, heteroscedasticity. Since we do not obtain detailed information about the possible measurement error, we use White period standard errors to account for heteroscedasticity (as in Weiß, Bostandzic and Neumann, 2014), as well as possible autocorrelation (see Petersen, 2009) in the regression's residuals.[19] Regression results are reported in Table 5. The upshot is that in both geographic regions, banks with larger size, higher leverage and lower tier 1 capital tend to be more systemically important in the following quarter. Even though systemic risk contributions in the regressions are standardised by the banks' asset value, size remains an important precursor. This suggests that larger banks are inherently more systemic regardless of their size. Our findings on the US sample are consistent with those of Hovakimian, Kane and Laeven (2012), Adrian and Brunnermeier (2008) based on CoVaR, Brownlees (2011) based on a "Hierarchical Factor GARCH" model and the sub-sample of well-capitalized banks in Lehar (2005).

Table 5 also indicates that in the US higher asset growth helps to reduce a bank's systemic risk contribution. However, US banks expanding too fast tend to be more systemically risky (which is captured by the quadratic asset growth term in the regression). Interestingly, the deposit ratio of a bank, measured as percentage of total assets, turns out to be insignificant with respect to its

[19] The time fixed effect dummies included in our regressions also help to remove the contemporaneous correlation between observations. Unreported robustness tests using alternative standard error specifications confirm that White period standard errors are the most conservative.

systemic risk contribution. Since deposits are deemed more stable in comparison with wholesale funding, due to deposit insurance, banks with higher deposit ratio are expected to have lower systemic risk. However, this could be offset by moral hazard as banks exploit deposit insurance by taking more risk (Acharya et al., 2009), especially when the deposit insurance premia do not fully reflect the inherent risk of the insured banks.

Surprisingly, asset liquidity, measured as the ratio between short term assets and total assets, has positive and significant impact on US banks' systemic risk contributions, while the coefficient is insignificant for European Banks. Possibly this is because the ratio in question may measure both liquidity and illiquidity. Clearly, short term assets are typically liquid. But during the recent crisis a lot of popular structured products (such as MBSs and CDOs) which were classified as short term, became illiquid.

It is of particular interest to examine further to what extent the differences between US and European banks are statistically significant. To do so, we conduct a regression analysis on all banks in our two regional samples with firm characteristics as explanatory variables plus their interaction with a US country dummy. As shown in Table 6, there are notable differences between the two regions. US banks' systemic risk contributions are more sensitive to their asset growth and liquidity, compared with their European counterparties. This may indicate that US banks were more involved in (exposed to) the innovations of financial instruments, such as securitization during the sample period. Overall, our findings support the newly proposed leverage ratio and enhanced capital requirement in Basel III. The prominence of size effects, when looking at both unstandardized and standardized measures of systemic risk, also suggests that curbing bank size, as emphasized in the Dodd-Frank Act in the US and the Vickers report in the UK, should rightly be a top priority.

In an unreported robustness test we introduce bank fixed effects, in addition to quarterly fixed effects. Adding such fixed effects removes cross-section variation and would reduce significance for some coefficients. For example the coefficient on the asset liquidity becomes insignificant for US banks as liquidity tends to vary much more in the cross-section than over time (see Loutskina and Strahan, 2009).

Finally, we extend our analysis by testing whether investment banking activities may contribute to systemic risk more than the conventional commercial banking business. We do so by considering in our regression analysis the ratio between non-interest income and net-interest income (N2I) as in Brunnermeier, Dong and Palia (2012). We also account for the impact of different elements of investment banking through the ratio between trading income and non-interest income (T2N). The results, which are restricted to the US sample for which we could source the relevant data, are reported in Table 7. The positive and significant coefficient of non-interest income when regressed alone (column 1) seems to support the idea that investment banking activities increase financial instability. However in the full model (column 3) such significance is lost, which is in line with Weiß, Bostandzic and Neumann (2014). More specifically, there is no evidence that the importance of trading income relative to other non-interest income may influence systemic risk.

6 Conclusion

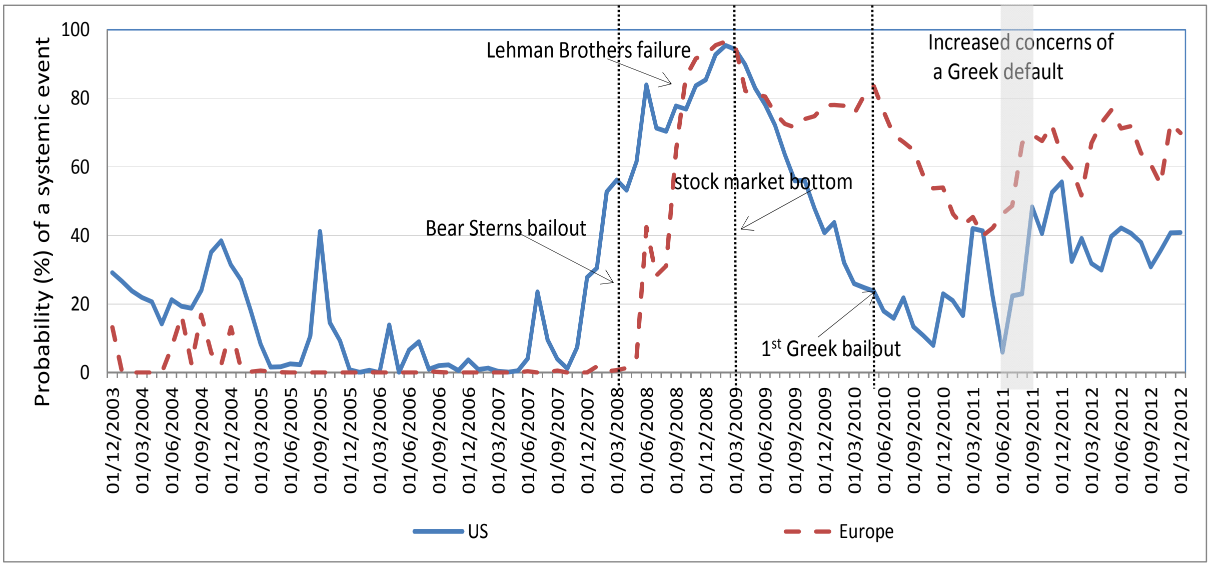
In this paper we investigate the evolution of systemic risk in the US and European banking industries at the aggregate level as well as for individual institutions over the 2004-2012 period. This includes both the subprime crisis and the European sovereign debt crisis which have characterised the longest and deepest recession since the Great Depression. We observe that although aggregate systemic risk peaked in March 2009 in the US as well as Europe, a new indicator of system fragility, based on the market perception of banks' short term indebtedness, suggests a degree of segregation between the two regions. The new indicator reveals that the most vulnerable point for European banks was during the more recent sovereign debt crisis.

We find that our ranking of most systemically important banks enables us to identify, 9 months before the Lehman default, the most systemically important US banks that later either defaulted and/or were acquired by competitors or received the largest government sponsored rescue packages. Interestingly, the extent of the capital injections in the 2011 Capital Purchase Program of the US government is significantly positively related to our ranking 6 months before the bailouts. We also observe that the capital injections are mainly allocated on the basis of bank size and do not appear to be affected by other factors that may influence systemic risk. This may be a cause for concern, as such factors were important in the Northern Rock failure which had major systemic consequences, though the bank in question was relatively small. Therefore, we propose a new standardised measure of systemic risk which enables us to control for the overshadowing effect of firm size. The new indicator appears to be better able to capture the systemic threat posed by smaller institutions and to predict the banks that were worst affected by the sub-prime crisis, both in the US and Europe.

It is of regulatory as well as academic interest to examine if one can predict an individual bank's contribution to systemic risk using balance sheet data. Our findings show that systemically riskier banks have larger size, lower tier1 capital and higher leverage. Therefore, our results support the regulatory response to the financial crisis embedded in the new Basel III agreement, including a proposed increase in capital requirements for systemically important banks and a new leverage ratio. Interestingly, we observe that firm characteristics appear to impact US and European banks differently.

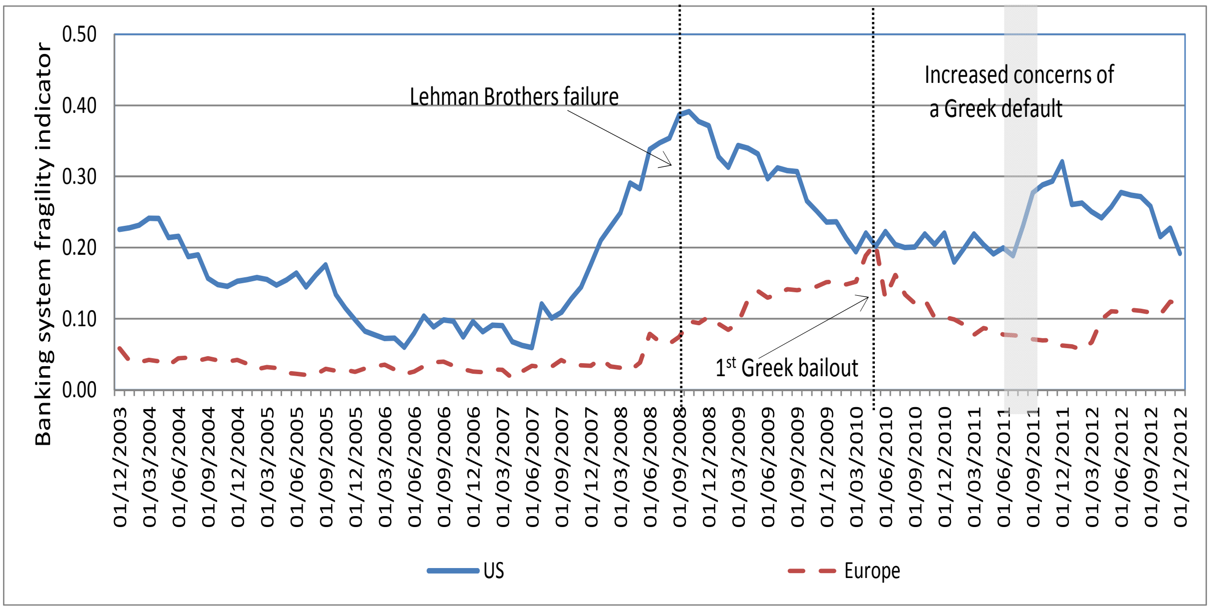
While our research focuses on banks, it could be easily extended to other financial institutions, such as insurance companies, broker dealers and government-sponsored enterprises, to gain an understanding of systemic risk in the whole financial industry. Moreover, the methodology we adopt could be used to determine how much extra capital or the size of financial penalties (e.g. in the form of a Pigouvian tax) that a systemically important bank should bear, which are interesting directions for future research.

Figure 1. Overall systemic risk in the US and European banking systems



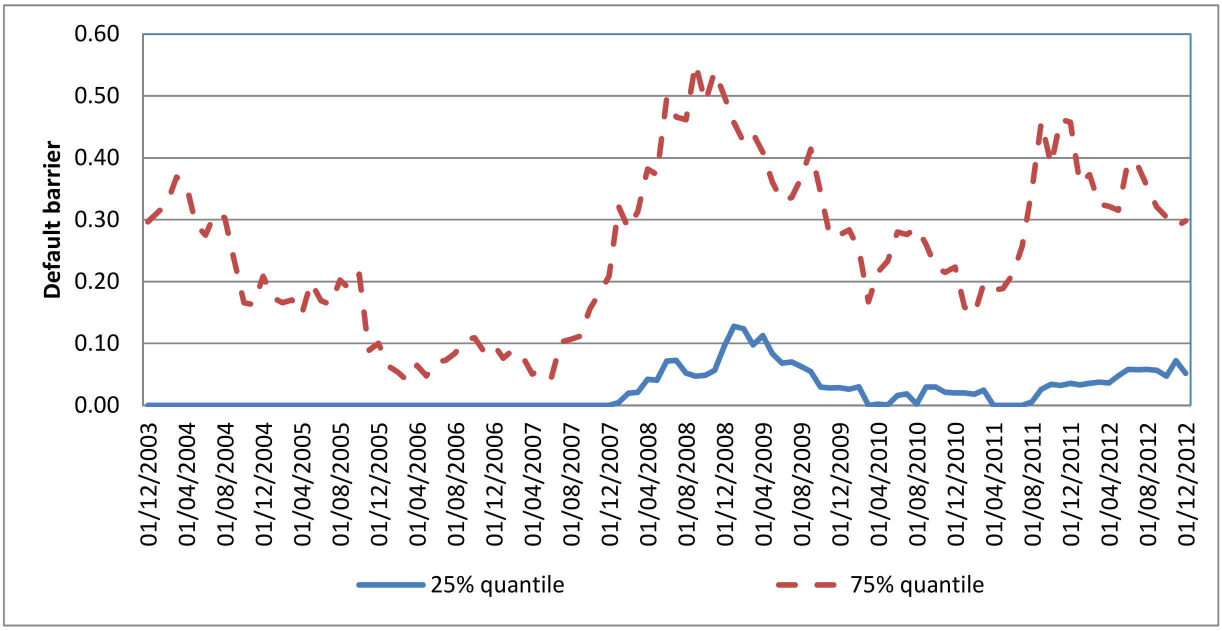
Systemic risk is measured as the probability (%) that the assets of the banks in distress exceed 10% of total bank assets over the next six months.

Figure 2. Banking system fragility indicator (BFI) in the US and Europe



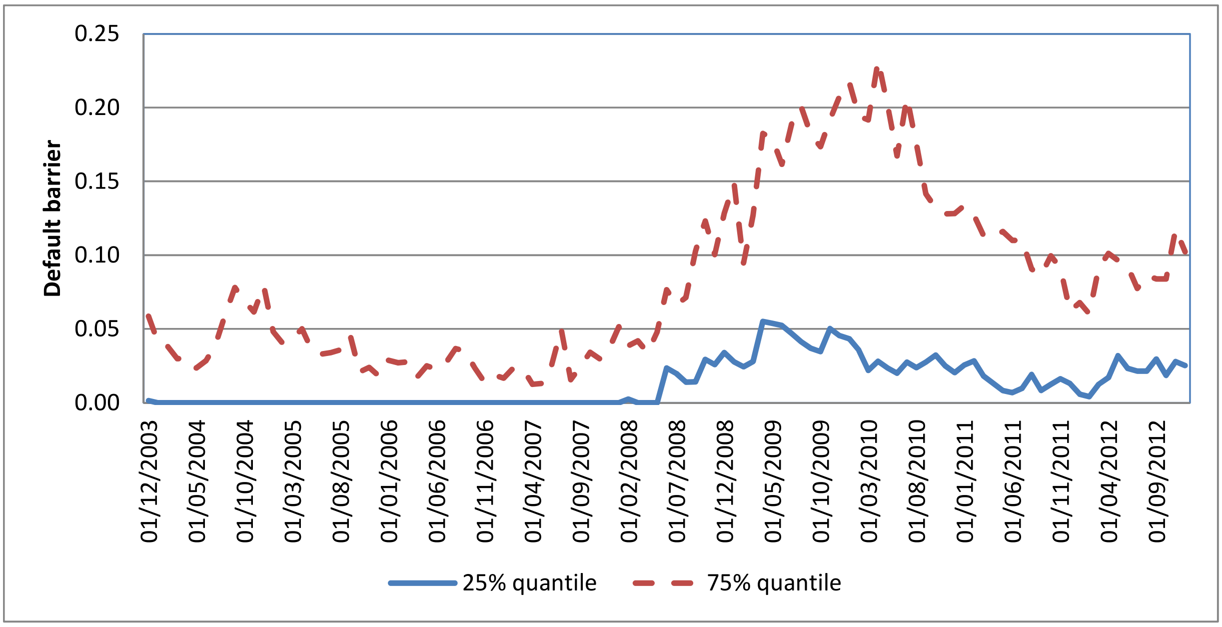
The BFI is the average default barrier across all banks in each region. Individual default barriers are estimated as a percentage of a bank's total liabilities.

Figure 3. Dispersion of default barriers in the US



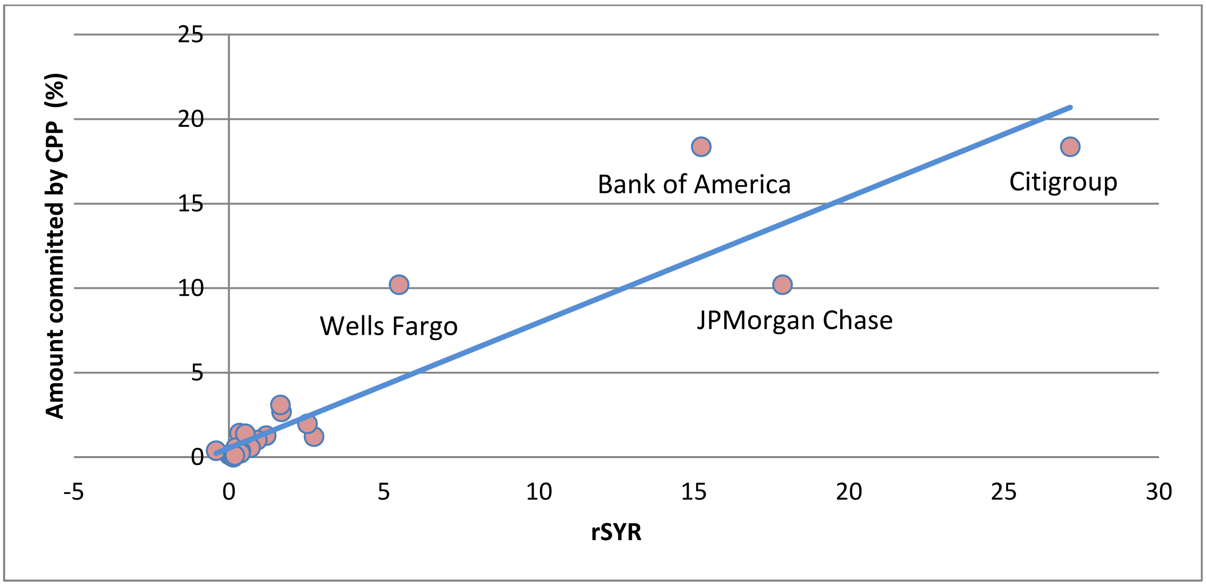
The Figures shows the 75% and 25% quantiles of the distribution of default barriers over the sample period.

Figure 4. Dispersion of default barriers in Europe



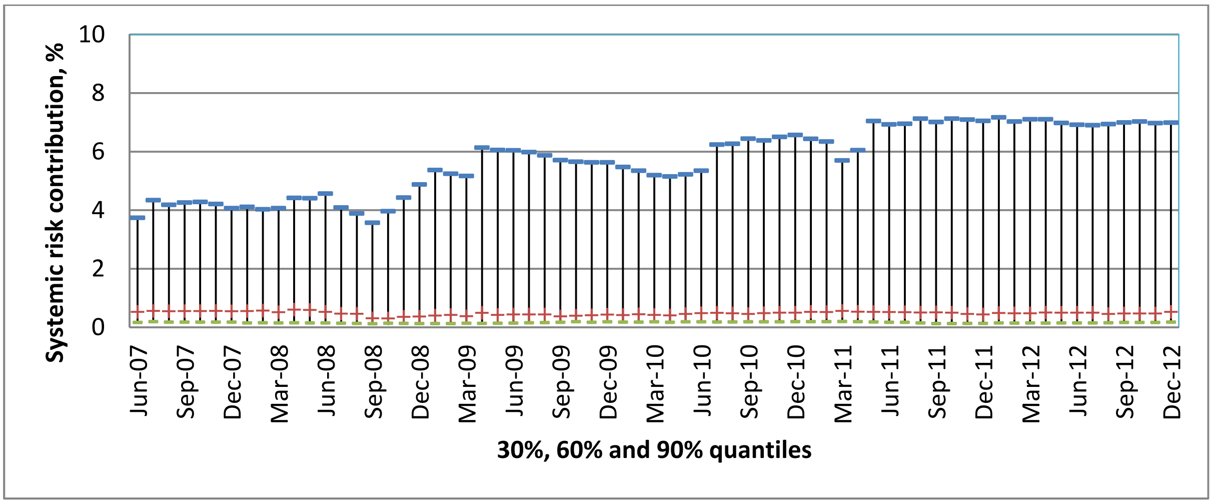
The Figures shows the 75% and 25% quantiles of the distribution of default barriers over the sample period.

Figure 5. Bank level relationship between US government capital injections and systemic risk



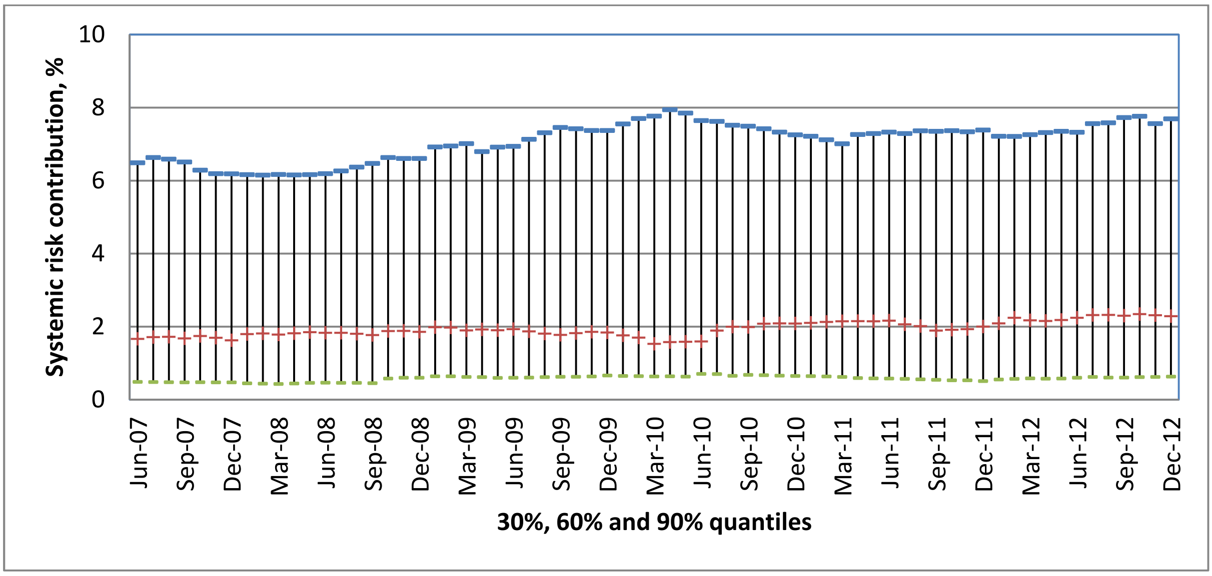
Scatterplot of the relative dollar amounts committed by the Capital Purchase Program (CPP) against our measure of bank specific systemic risk (rSYR).

Figure 6. Distribution of systemic risk contributions for US banks



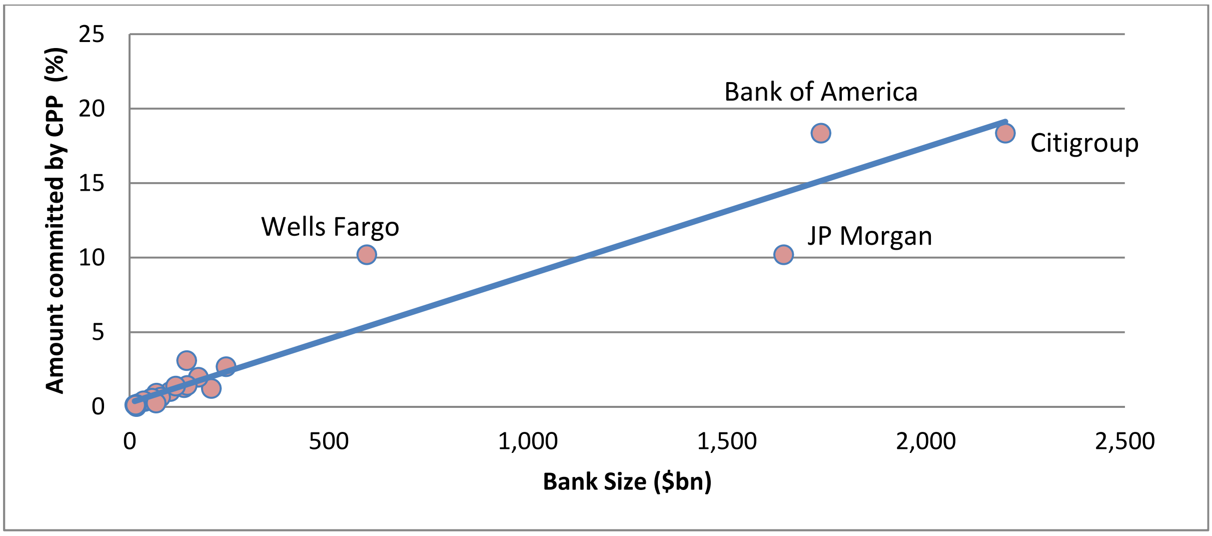
We report 90%, 60% and 30% quantiles over the crisis period.

Figure 7. Distribution of systemic risk contributions for European banks



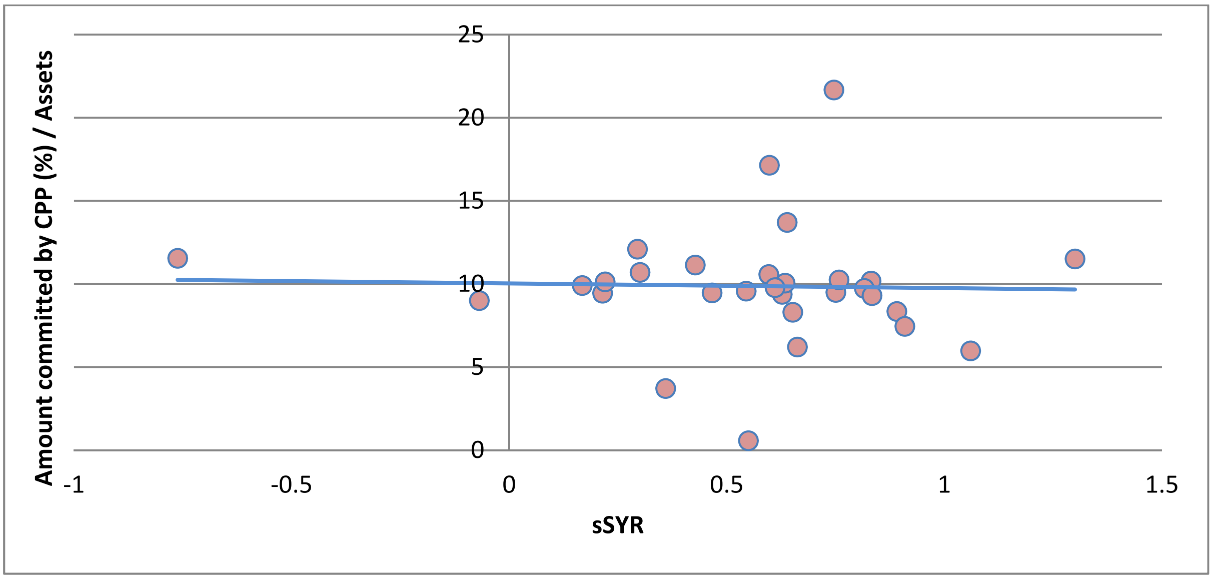
We report 90%, 60% and 30% quantiles over the crisis period.

Figure 8. Bank level relationship between US government capital injections and bank size



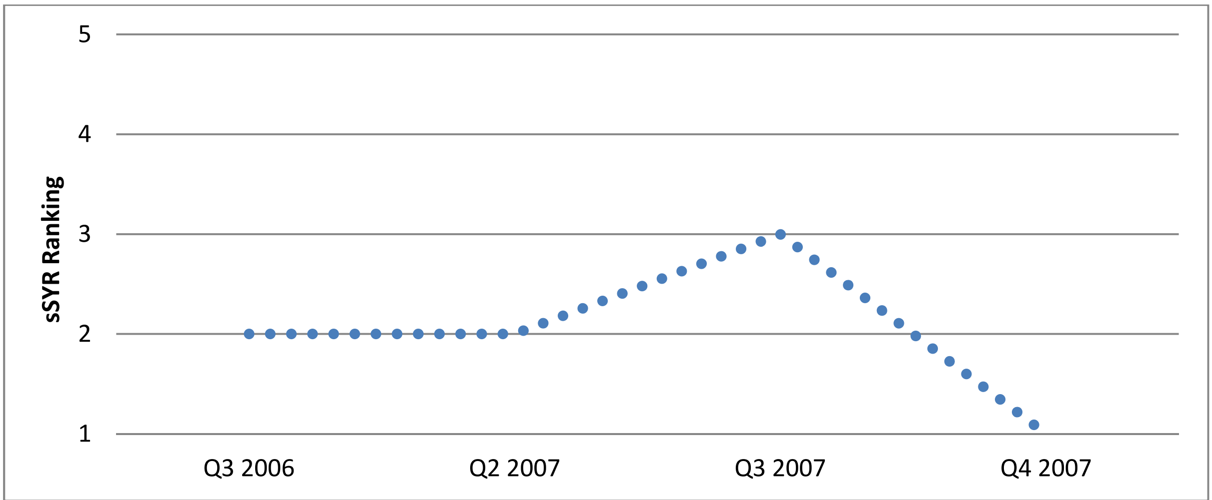
Scatterplot of the relative dollar amounts committed by the Capital Purchase Program (CPP) against bank size measured by total assets.

Figure 9. Bank level relationship between US government capital injections and standardised systemic risk



Scatterplot of the relative dollar amounts committed by the Capital Purchase Program (CPP) against the standardised systemic risk indicator sSYR.

Figure 10. Northern Rock's systemic risk ranking before its bailout



The rankings in the graph are measured with our standardised systemic risk indicator, sSYR, relative to all European banks in our sample.

Table 1. Rankings of systemically important banks

In the Table we report the rankings of systemically important banks in the US (panel A) and Europe (panel B) at year-end 2007 and 2011 according to the following measures: Relative systemic risk (rSYR), standardised systemic risk (sSYR) and the Acharya, Engle and Richardson (2012) indicator (AER). Banks included in the list of "systemically important financial institutions" drawn by the Financial Stability Board (FSB) are labelled with a "Y". Banks with an asterisk defaulted or were acquired during the financial crisis.

Panel A: United States

	2007 Rankings				2011 Rankings				
Bank	Asset value Q4 2007 (bn USD)	rSYR	sSYR	AER	Asset value Q4 2011 (bn USD)	rSYR	sSYR	AER	FSB
Citigroup	2,187	1	6	1	1,874	3	3	3	Y
Bank of America	1,716	2	25	3	2,129	2	1	1	Y
JPMorgan Chase	1,562	3	20	2	2,266	1	2	2	Y
Wachovia*	783	4	9	4	-	-	-	-	
Wells Fargo & Co	575	5	34	6	1,314	4	14	4	Y
Washington Mutual*	328	6	16	5	-	-	-	-	
Suntrustbanks	171	7	1	11	177	8	5	6	
Bank NY Mellon	198	8	2	27	325	6	24	5	Y
US Bancorp	238	9	42	26	340	5	13	13	
Natl City*	150	10	27	7	-	-	-	-	
Regions Financial	141	11	19	15	127	18	34	7	
PNC Financial	139	12	22	18	271	7	18	8	
BB&T	133	13	21	10	175	9	8	9	
Sovereign Bancorp*	84	14	8	8	-	-	-	-	
Keycorp	98	15	33	9	89	11	17	10	
Northern Trust	67	16	28	25	100	10	12	12	
Comerica	62	17	24	14	61	17	27	15	
Huntington Banc.	55	18	12	13	54	16	23	16	
Fifth Third Banc.	111	19	44	12	117	13	29	11	
Commerce Banc. NJ*	49	20	11	21	-	-	-	-	
M & T Bank Corp	65	22	40	19	78	12	16	19	
First Horizon NA	37	23	14	-	25	34	33	-	
Indymac Bancorp*	33	24	5	-	-	-	-	-	
Zions Bancorp	53	25	43	16	53	15	19	14	
Flagstar Bancorp	16	31	4	-	14	31	26	-	
First Citizens-A	16	33	7	-	21	21	6	-	
Bankunited Fin-A*	14	34	3	-	-	-	-	-	
Downey Finl Corp*	13	37	10	-	-	-	-	-	
Citizens Republi.	14	38	15	-	9	30	4	-	
Sterling Finl/WA	12	40	13	-	9	32	10	-	
Hudson City Bncp	44	45	47	24	45	14	7	17	

Table 1 – continued

Panel B: Europe

Bank	2007 Rankings Asset value Q4 2007 (bn USD)	rSYR	sSYR	AER	2011 Rankings Asset value Q4 2011 (bn USD)	rSYR	sSYR	AER	FSB
RBS	3,650	1	15	1	2,337	5	10	5	Y
Deutsche Bank-RG	2,946	2	3	2	2,805	1	7	1	Y
Barclays Plc	2,434	3	2	3	2,425	2	5	4	Y
BNP Paribas	2,471	4	6	4	2,547	3	22	2	Y
HSBC	2,354	5	26	12	2,556	4	27	6	Y
Credit Agricole	2,062	6	5	5	2,234	6	6	3	Y
UBS	2,003	7	9	6	1,512	10	24	9	Y
Societe Generale	1,563	8	7	7	1,531	8	16	7	Y
Unicredit Spa	1,490	9	21	15	1,201	11	13	11	Y
HBOS Plc*	1,323	10	8	8	-	-	-	-	
Banco Santander	1,331	11	28	14	1,622	7	15	10	Y
Credit Suiss-Reg	1,198	12	17	10	1,118	12	12	12	
Commerzbank	899	13	4	9	858	14	2	13	Y
Dexia SA	882	14	10	11	535	18	1	17	Y
Natixis	758	15	11	13	658	16	3	16	
Intesa Sanpaolo	836	16	34	34	828	15	33	15	
Lloyds Banking	701	17	18	16	1,505	9	14	8	Y
Nordea	567	19	22	17	928	13	19	14	Y
SEB AB-A	362	22	13	-	343	24	34	-	
Northern Rock*	217	28	1	-	-	-	-	-	
Alliance & Leice.*	157	32	12	-	-	-	-	-	
Bradford & Bing.*	103	37	14	-	-	-	-	-	

Table 2. Relationship between US government capital injections and banks' systemic risk

The dependent variable in the regressions reported in the Table is the proportional capital injection received by 30 banks included in the Capital Purchase Program of the US government as part of the Troubled Assets Relief Program started in October 2008 (models 1 and 2), and the standardised injection, i.e. the dollar value of the injection divided by the total asset value of each recipient bank 6 months before the start of the Program (models 3 and 4). The explanatory variables include our measure of the banks' systemic importance, rSYR, the standardised value of the same, sSYR, and bank characteristics, all lagged by 6 months. Bank characteristics include: Assets Growth defined as quarterly growth of total assets; Leverage given by total assets over equity; Liquidity equal to short term assets divided by total assets; and the Deposit Ratio computed as a percentage of total assets. *** and ** denote significance at the 1% and 5% level. t-values have been computed with White standard errors.

Dependent variable: Capital injection

	Proportional Injection		Standardised Injection	
	Model 1	Model 2	Model 3	Model 4
Constant	0.54**	0.07	2.58***	6.79**
$rSYR_{t-1}$	0.74***	–0.29		
$sSYR_{t-1}$			–0.00	0.01
Total $Assets_{t-1}$		0.01***		0.00
Assets $Growth_{t-1}$		–0.28		–0.20
Assets Growth2 t-1		0.02		0.02**
Tier 1 $Ratio_{t-1}$		–0.12		–0.30**
$Leverage_{t-1}$		0.09		–0.05
$Liquidity_{t-1}$		–0.04		–0.03
Return on $Assets_{t-1}$		0.50		0.53
Deposit $Ratio_{t-1}$		0.01		–0.02
Adjusted R-squared	0.849	0.910	–0.028	0.077
Observations	30	30	30	30

Table 3. High distress prediction: sSYR vs. rSYR

In the Table we report pre-crisis systemic risk rankings (1=highest), as of 2007Q2, from our standardised (sSYR) and unstandardised (rSYR) systemic risk measures for the 15 most distressed banks in Europe and the US. In the group we include institutions that either had the largest stock price contractions during the sub-prime crisis period (2007Q3 to 2009Q1), or were delisted due to nationalisation, default or merger (denoted with "na"). The % Dominance of a systemic risk measure indicates the proportion of banks for which that measure shows higher systemic risk (lower ranking value) than the other measure. The average gap for a systemic risk measure is the average ranking difference relative to the other measure when the former dominates.

United States				Europe			
Bank	Fall in stock price (%)	sSYR ranking	rSYR ranking	Bank	Fall in stock price (%)	sSYR ranking	rSYR ranking
Bankunited Fin-A	na	4	34	Alliance & Leice	na	14	31
BBVA Usa Bancshs	na	40	26	Bradford & Bing	na	32	36
Commerce Banc NJ	na	8	18	HBOS Plc	na	7	9
Downey Finl Corp	na	11	36	Irish Bank Resol	na	22	33
First Republic	na	10	42	Northern Rock	na	2	26
Indymac Bancorp	na	5	25	Allied Irish BK	97%	29	27
Natl City Corp	na	7	10	Bank Ireland	96%	19	23
Sovereign Bancorp	na	24	15	Swedbank AB-A	91%	36	30
Unionbancal Corp	na	25	20	RBS	88%	13	5
Wachovia Corp	na	16	4	KBC Group	88%	25	20
Washington Mutual	na	9	6	Commerzbank	84%	3	13
Colonial Bancgro	95%	31	28	Natixis	83%	10	15
Citigroup	95%	6	1	Dexia SA	83%	8	14
South Financial	94%	28	43	Banco Com Port-R	81%	37	35
Sterling Finl/WA	93%	14	46	Barclays Plc	80%	6	2
Average		**15.9**	**23.6**	**Average**		**17.5**	**21.3**
Average Gap		20.9	7.3	Average Gap		9.2	4.5
% Dominance		53%	47%	% Dominance		60%	40%

Table 4. Summary statistics of regression variables.

The following Table shows summary statistics (panel A) and pairwise correlations (panel B) for the banks in our sample. Total assets growth is the quarterly return of the banks' total assets; Tier 1 ratio is the ratio of tier 1 capital to risk weighted assets; Leverage is computed as total assets over total common equity; Asset Liquidity is short-term assets over total assets; Return on Assets (ROA) is calculated as net income divided by total assets; the Deposit Ratio is deposits over total assets; sSYR is our measure of standardized systemic risk. Sample period: Q1 2004 to Q4 2012. All variables (excluding sSYR) are winsorised at 5% and 95%.

Panel A: Summary statistics

	Total Assets (bn USD)	Assets Growth (%)	Tier 1 Ratio (%)	Leverage	Asset Liquidity (%)	ROA (%)	Deposit Ratio (%)
				Whole Sample			
Mean	438.78	1.52	10.02	18.54	29.22	0.58	52.46
Median	122.69	1.17	9.61	14.72	25.82	0.66	52.78
Max	2,469.87	11.29	15.09	52.85	67.69	1.78	84.22
Min	10.63	–5.87	6.60	7.73	8.93	–1.72	18.24
Std. Dev.	645.04	3.84	2.32	10.61	14.54	0.72	18.74
Skewness	1.81	0.47	0.46	1.54	0.96	–1.09	–0.08
Kurtosis	5.33	3.05	2.18	4.95	3.24	4.60	1.90
Obs.	2,758	2,758	2,758	2,758	2,758	2,758	2,758
				US Sample			
Mean	177.75	1.45	10.21	11.54	25.47	0.78	67.00
Median	30.99	1.13	9.95	11.02	22.53	0.97	67.96
Max	1,483.20	8.71	14.35	17.81	53.16	1.78	84.22
Min	10.63	–4.06	7.07	7.73	8.93	–1.72	43.06
Std. Dev.	379.56	3.16	2.12	2.60	12.24	0.84	11.44
Skewness	2.80	0.53	0.35	0.85	0.91	–1.58	–0.52
Kurtosis	9.41	2.98	2.04	3.19	2.97	5.17	2.59
Obs.	1,486	1,486	1,486	1,486	1,486	1,486	1,486
				European Sample			
Mean	701.16	1.65	9.68	25.71	32.84	0.44	37.59
Median	323.99	1.28	9.10	23.06	29.58	0.47	37.38
Max	2,469.87	11.29	15.09	52.85	67.69	1.29	58.26
Min	60.77	–5.87	6.60	12.21	12.46	–0.72	18.24
Std. Dev.	743.90	4.46	2.43	10.91	15.68	0.49	11.77
Skewness	1.22	0.37	0.72	0.99	0.84	–0.55	0.10
Kurtosis	3.28	2.63	2.53	3.28	2.81	3.17	1.89
Obs.	1,272	1,272	1,272	1,272	1,272	1,272	1,272

Table 4 - Continued

Panel B: Pairwise correlations

	sSYR	Log (Total Assets)	Assets Growth	Tier 1 Ratio	Leverage	Asset Liquidity	ROA
				Whole Sample			
Log(Total assets)	0.47						
Total assets growth	0.00	0.03					
Tier1 ratio	–0.15	–0.04	–0.16				
Leverage	0.47	0.55	–0.01	–0.10			
Asset liquidity	0.27	0.50	0.10	0.16	0.37		
ROA	–0.24	–0.14	0.29	–0.18	–0.28	–0.04	
Deposit ratio	–0.48	–0.68	–0.07	0.17	–0.71	–0.38	0.20
				US Sample			
Log(Total assets)	0.23						
Total assets growth	0.00	0.05					
Tier1 ratio	–0.13	–0.12	–0.15				
Leverage	0.20	–0.05	0.06	–0.25			
Asset liquidity	0.18	0.39	0.17	0.21	0.08		
ROA	–0.12	0.07	0.30	–0.25	–0.22	0.08	
Deposit ratio	–0.17	–0.42	–0.12	0.41	–0.21	–0.19	0.00
				European Sample			
Log(Total assets)	0.36						
Total assets growth	–0.06	–0.05					
Tier1 ratio	–0.07	0.24	–0.14				
Leverage	0.49	0.40	–0.08	0.06			
Asset liquidity	0.23	0.56	0.05	0.20	0.37		
ROA	–0.32	–0.25	0.35	–0.23	–0.35	–0.12	
Deposit ratio	–0.31	–0.41	0.02	–0.21	–0.52	–0.43	0.26

Table 5. Systemic risk precursors

In this table we show results of panel regressions of bank specific systemic risk (standardised by the bank's total assets), sSYR, on a set of lagged bank characteristics. These include Size measured as log of total assets; Assets Growth given by the quarterly return of total assets; Tier1 ratio which is the ratio of tier1 capital to risk weighted assets; Leverage computed as total assets over total common equity; Liquidity equal to short-term assets over total assets; Return on Assets calculated as net income divided by total assets; and Deposit Ratio which is deposits over total assets. Sample period: Q1 2004 to Q4 2012. A winsorisation at the 5% and 95% quantiles is used to control for the outliers of the independent variables. *** denotes significance at the 1% level. t-values have been computed with White period (heteroscedasticity and autocorrelation robust) standard errors.

Panel A: United States

Dependent variable: sSYR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	15.81	60.07***	91.67***	34.91***	52.05***	67.77***	92.79***	34.20
$Size_{t-1}$	4.29***							3.11***
Assets $growth_{t-1}$		−1.85***						−1.18***
Assets growth2 t-1		0.40***						0.23***
Tier1 $ratio_{t-1}$			−2.90***					−2.45***
$Leverage_{t-1}$				2.36***				1.26**
$Liquidity_{t-1}$					0.40**			0.30**
Return on $assets_{t-1}$						−7.07***		−6.00***
Deposit $ratio_{t-1}$							−0.46***	0.01
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.084	0.067	0.064	0.081	0.064	0.062	0.070	0.198
Observations	1486	1486	1486	1486	1486	1486	1486	1486

Table 5 - Continued

Panel B: Europe

Dependent variable: sSYR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	34.06***	83.58***	89.85***	69.00***	78.05***	89.50***	96.22***	61.27***
$Size_{t-1}$	3.97***							2.32***
Assets $growth_{t-1}$		-0.58***						-0.05
Assets growth2 t-1		0.06***						0.01
Tier1 $ratio_{t-1}$			-0.62					-1.30**
$Leverage_{t-1}$				0.58***				0.42***
$Liquidity_{t-1}$					0.18***			-0.02
Return on $assets_{t-1}$						-12.30***		-3.85
Deposit $ratio_{t-1}$							-0.33***	-0.06
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.157	0.036	0.027	0.279	0.070	0.177	0.118	0.369
Observations	1272	1272	1272	1272	1272	1272	1272	1272

Table 6. Systemic risk precursors – combined sample.

In this table we show results of panel regressions of bank specific systemic risk (standardised by the bank's total assets), sSYR, on a set of lagged bank characteristics for the combined sample of US and European banks. These include: Size measured as log of total assets; Assets Growth given by the quarterly return of total assets; Tier1 ratio which is the ratio of tier1 capital to risk weighted assets; Leverage computed as total assets over total common equity; Liquidity equal to short-term assets over total assets; Return on Assets calculated as net income divided by total assets; Deposit Ratio computed as deposits over total assets; and US which is a country dummy equal to 1 for US banks and 0 otherwise. Sample period: Q1 2004 to Q4 2012. A winsorisation at the 5% and 95% quantiles is used to control for the outliers of the independent variables. ***, ** and * denote significance at the 1%, 5% and 10% level. t-values have been computed with White period (heteroscedasticity and autocorrelation robust) standard errors.

Dependent variable: sSYR

	Lag of explanatory variables:	
	One Quarter	Half Year
Constant	44.16***	44.45***
Size	3.43***	3.35***
Assets growth	–0.04	–0.14
Assets growth^2	0.02	0.01
Tier1 ratio	–1.46***	–1.38***
Leverage	0.48***	0.48***
Liquidity	–0.06	–0.05
Return on assets	–2.98	–2.14
Deposit ratio	0.01	0.00
US*Size	–0.72	–0.76
US*Assets growth	–1.35***	–0.92***
US*Assets growth^2	0.23***	0.19***
US*Tier1 ratio	–1.01	–1.21
US*Leverage	0.54	0.77
US*Liquidity	0.38**	0.37**
US*Return on Assets	–2.64	–3.84
US*Deposit ratio	–0.06	–0.05
Time fixed effects	Yes	Yes
Adjusted R-squared	0.383	0.387
Observations	2566	2473

Table 7. Regression of a bank's systemic risk on non-interest income for US banks

In this table we show results of panel regressions of bank specific systemic risk (standardised by the bank's total assets), sSYR, on non-interest income and its trading income component. Non-interest income is measured as the non-interest income to net-interest income ratio (N2I) and trading income is measured as the trading income to non-interest income ratio (T2N). We also include a set of lagged bank characteristics: Size, measured as log of total assets; Assets Growth given by the quarterly return of total assets; Tier1 ratio which is the ratio of tier1 capital to risk weighted assets; Leverage computed as total assets over total common equity; Liquidity equal to short-term assets over total assets; Return on Assets calculated as net income divided by total assets; and Deposit Ratio which is deposits over total assets. Sample period: Q1 2004 to Q4 2012. A winsorisation at the 5% and 95% quantiles is used to control for the outliers of the independent variables. *** and ** denote significance at the 1% and 5% level. t-values have been computed with White period (heteroscedasticity and autocorrelation robust) standard errors.

Dependent variable: sSYR

	(1)	(2)	(3)
Constant	59.89***	59.88***	34.51**
$Size_{t-1}$			3.15***
Assets $growth_{t-1}$			–1.20***
Assets growth2 t-1			0.24***
Tier1 $ratio_{t-1}$			–2.45***
$Leverage_{t-1}$			1.25**
$Liquidity_{t-1}$			0.34**
Return on $assets_{t-1}$			–5.87***
$N2I_{t-1}$	0.03**	0.03**	–0.01
$T2N_{t-1}$		0.00	0.00
Time fixed effects	Yes	Yes	Yes
Adjusted R-squared	0.037	0.037	0.198
Observations	1486	1486	1486

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