Systemic Risk in the US and European Banking Sectors in Recent Crises

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Abstract

In this paper we measure systemic risk in the banking sector by taking into account relevant bank characteristics such as size, leverage and interconnectedness. We analyse both aggregate and individual systemic risk for US and European banks. At the aggregate level, a new indicator of banking system fragility based on the "effective" level of short term debt in the industry reveals markedly different systemic risk patterns in the US and Europe over time. At the firm level, 9 months before the Lehman Brothers failure we are able to identify the most systemically important US banks that later either defaulted or received the largest bailouts from the US Treasury. We also find that a bank's balance sheet characteristics can help to predict 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.

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1. Introduction

"Systemic risk can be broadly characterised as the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially".[2]

--------The European Central Bank (2010)

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.

[2] While the importance of managing systemic risk is well understood by both regulators and academics, a consensus on the definition of systemic risk is yet to be reached. Other working definitions are those in use by the Bank for International Settlements (1994), Adrian and Brunnermeier (2008), the Financial Stability Board (2009) and Billio, Getmansky, Lo and Pelizzon (2012), among others.

A variety of systemic risk measures has been proposed since the financial 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).[3] 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. (2013) observe that 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.

Acharya, Pedersen, Philippon and Richardson (2010) propose a measure of systemic risk (Systemic Expected Shortfall) based on an explicit economic model. This has been adopted by Brownlees and Engle (2011) and Acharya, Engle and Richardson (2012) to propose a new systemic risk indicator (hereafter AER) that captures a financial institution’s contribution to the total capital shortfall of the financial system. Principal component analysis and Granger-

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

causality tests have also been utilized to measure the degree of commonality and interconnection in a group of financial firms and hence the 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) and Suh (2012), which adopt a structural approach based on contingent claim analysis to identify systemically important banks. Using CDS market data, Huang, Zhou and Zhu (2009) and Black et al. (2013) measure the systemic risk of the banking sector as a hypothetical distress insurance premium. On the other hand, Patro, Qi and Sun (2013) find that systemic risk is related to the level of correlation among the idiosyncratic components of financial institutions' stock returns.

In line with Lehar (2005) and Suh (2012), we apply contingent claim analysis to measure systemic risk. The idea is to look at equity as a call option on a bank's total assets, which is based on the corporate default model originally proposed by Merton (1974). Monte Carlo simulations are then employed to produce bank asset dynamics and individual banks' contributions to systemic risk.

This paper contributes to the existing literature in four ways. First, 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).

Our second 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.[4] 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).[5] Although our results are largely consistent with AER, we believe our approach deals better with the definition of a distress condition. More specifically, our approach can explicitly define an individual bank's default, and hence a distress condition more relevant to systemic risk. In Acharya, Engle and Richardson (2012), to calculate AER, a financial crisis is defined as 40% 6-month cumulative decline of stock market index, however not all large drops in equity markets trigger a financial systemic crisis, such as the burst of the Internet bubble in the early 2000s. In contrast, we model a financial crisis as an event which occurs when the proportion of the assets of distressed banks to the total assets of all banks exceeds a certain threshold, which directly leads to a financial distress. While our definition of a financial crisis is also sensitive to stock market return, a big drop in market index itself is not enough to be qualified as a crisis event in our model (although it is for AER), since the vulnerability of the banking system (e.g. average leverage) is also

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

[5] 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".

important. For example, if the leverage is low enough, then banks would not default even if stock market plummets. Even effective risk management framework/regulation framework within the banking system would be possible to help banks withstand stock market shocks and thus avoid a financial crisis. As long as banks can survive big shocks in the market, there shocks are not treated as a crisis event in our setting. In short, our treatment is more relevant and target-oriented.

Our third 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 and profitability. Our intent is to see whether such drivers could be employed to design effective regulation and government policies to curb systemic risk. Fourth, we expand the sample period of previous studies to cover both the subprime crisis of 2007-2009 and the sovereign crisis started in 2010 to examine systemic risk in the US and Europe.

Our analysis shows 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 period (availability of emergency central bank funding, government sponsored bail outs, capital injections and so on).

We also find that systemically important banks, identified by using our method, 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. Apart from bank size, we observe that capital injections did not take into account the other factors that influence systemic risk, e.g. interconnectedness and default risk. This may be a cause for concern as both factors were important in the Northern Rock and Lehman Brothers failures which had major systemic consequences. Besides, Northern Rock was relatively small compared to its peers, which indicates that size is not necessarily the most prominent determinant of systemic risk.

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 higher tier 1 capital and a new leverage constraint for systemically important banks.

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

2. 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, similar 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]

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:

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

[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.

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:

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

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 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).

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

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

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

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]

$$Overall\ systemic\ risk_t = Prob[Crisis]$$
$$= Prob[\textstyle\sum_{i}(A_{i,t+1}\,|A_{i,t+1} < \delta_{i,t}L_{i,t+1}) > \theta \textstyle\sum_{i} A_{i,t+1}] \quad (5)$$

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

[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:

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

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:

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

[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.

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 (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.

3. 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]

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

4. Empirical findings

We first apply the methodology explained in Section 2 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). Lastly, we use a fixed effects panel regression to illustrate how a bank's characteristics can help us to predict its systemic importance.

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 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

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

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 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.

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

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[14] AER measures are available at http://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.

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. 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). To answer the above, 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 banks, on our standardised systemic risk measure sSYR (Table 2, models 3 and 4). Again, the relationship is not statistically significant, though 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.

When looking at rankings of European banks (Table 1 Panel B) and comparing them with the SIFIs identified by the FSB in November 2011, it appears that we capture almost all systemically important banks. Dexia, which was repeatedly bailed out by the French and Belgian governments, is 14th in our 2007 relative rankings (rSYR) but only 18th in 2011. However, remarkably, according to our 2011 standardised ranking (sSYR) it ranks first as does Northern Rock in 2007, both of which indicate the ability of the indicator to pick up systemically important institutions despite their relatively smaller size.

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 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 3 contains summary statistics of our regression variables and their pairwise correlations for the US (Panel A) and Europe (Panel B). 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. Regression results are reported in Table 4. The upshot is that in both geographic regions, banks with higher leverage, lower tier 1 capital and lower profitability 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 but only for the United States. This suggests that larger US banks are inherently more systemic regardless of their size. Our findings on the US sample are consistent with those of 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 4 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 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, Philippon, Richardson and Roubini, 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 no significant impact on both regions' systemic risk contributions. 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 very illiquid.

It is of particular interest to further examine 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 leverage and asset growth, compared with their European counterparties. Overall, our findings support the newly proposed leverage ratio and enhanced capital requirement in Basel III. The prominence of size effects, when looking at unstandardized 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.

5 Conclusions

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.

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, higher leverage and lower profitability. 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 leverage and asset growth 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 overall picture 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) a systemically important bank should bear, which are interesting directions for future research.

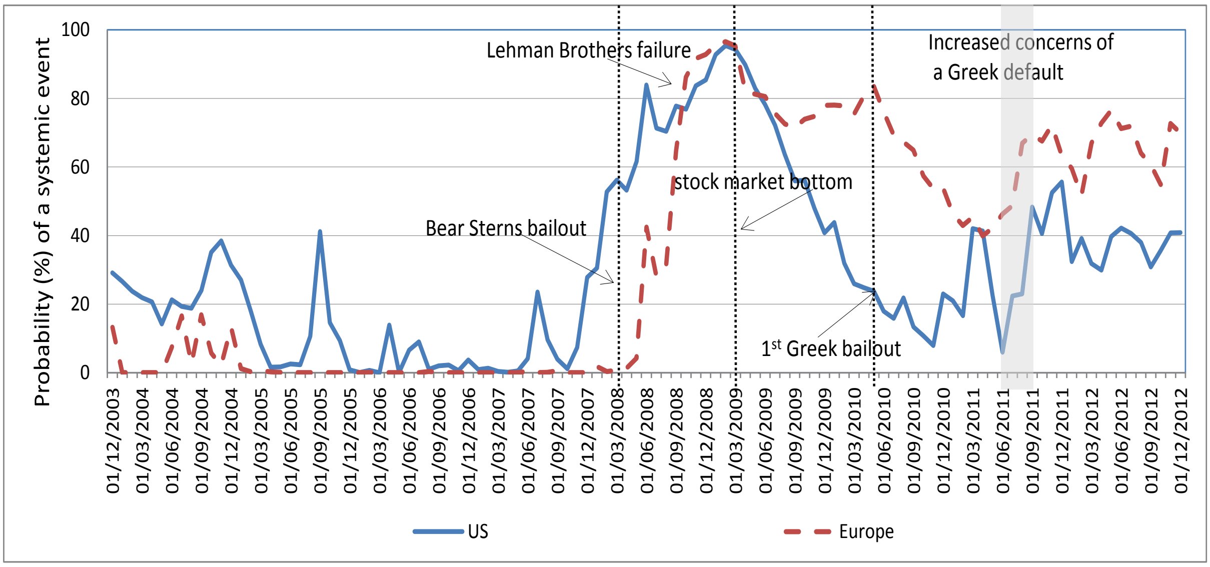

Figure 1. Overall systemic risk in the US and European banking systems. Systemic risk is measured as the probability (%) that the assets of the banks in distress exceed 10% of total bank assets over the next six months.

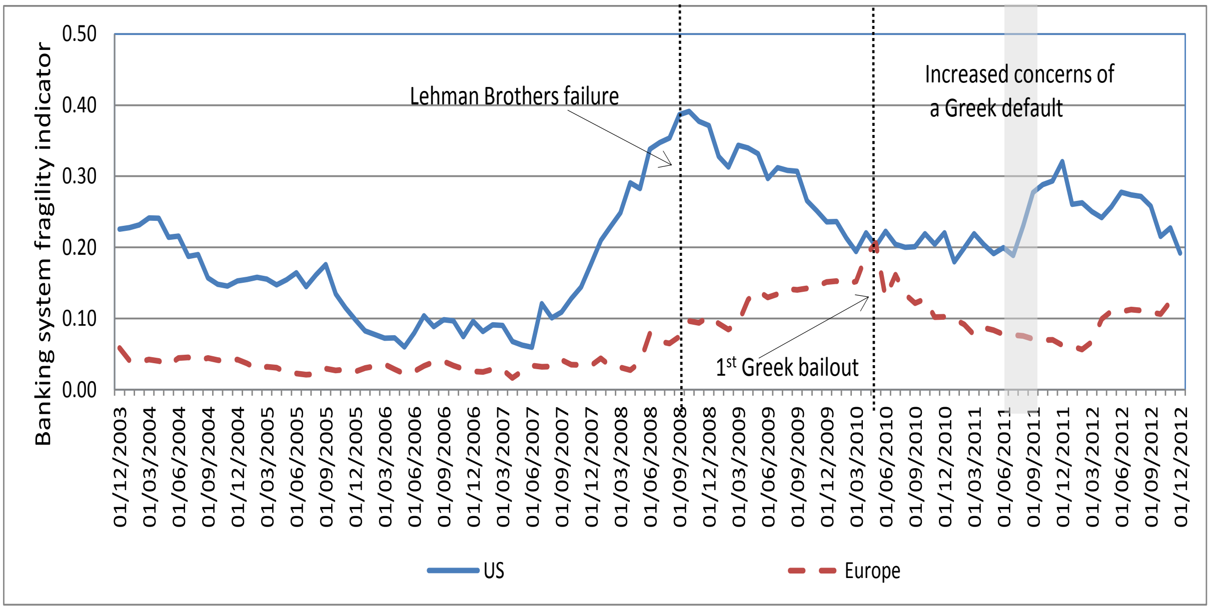

Figure 2. Banking system fragility indicator (BFI) in the US and Europe. The BFI is the average default barrier across all banks in each region. Individual default barriers are estimated as a percentage of a bank's total liabilities.

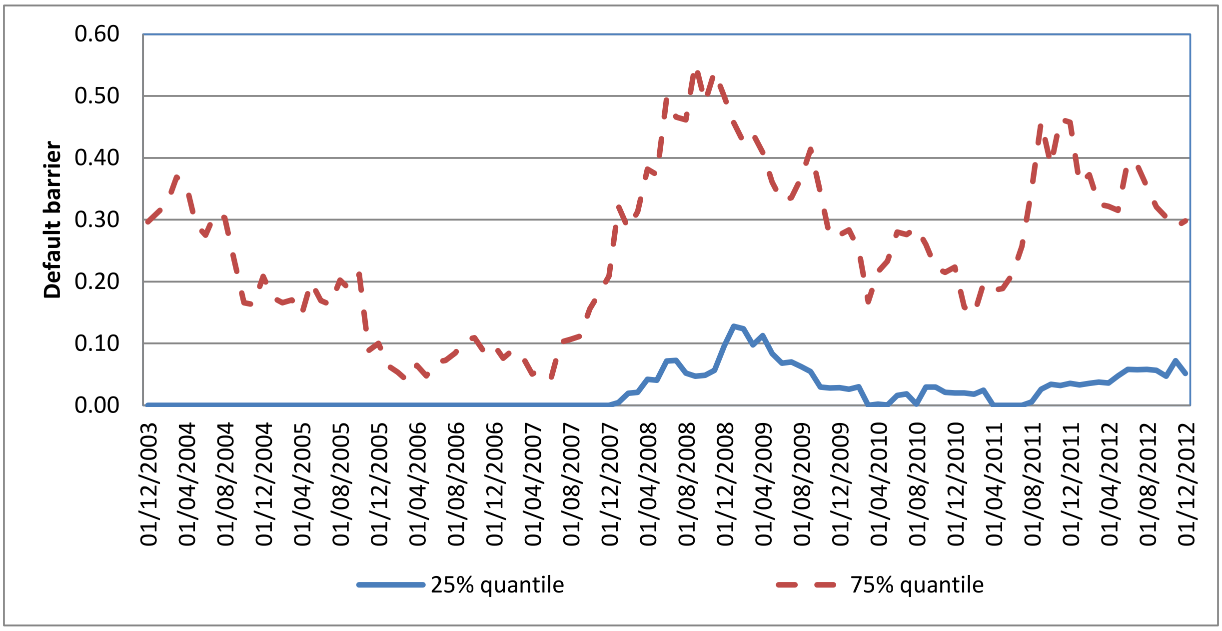

Figure 3. Dispersion of default barriers in the US. The Figures shows the 75% and 25% quantiles of the distribution of default barriers over the sample period.

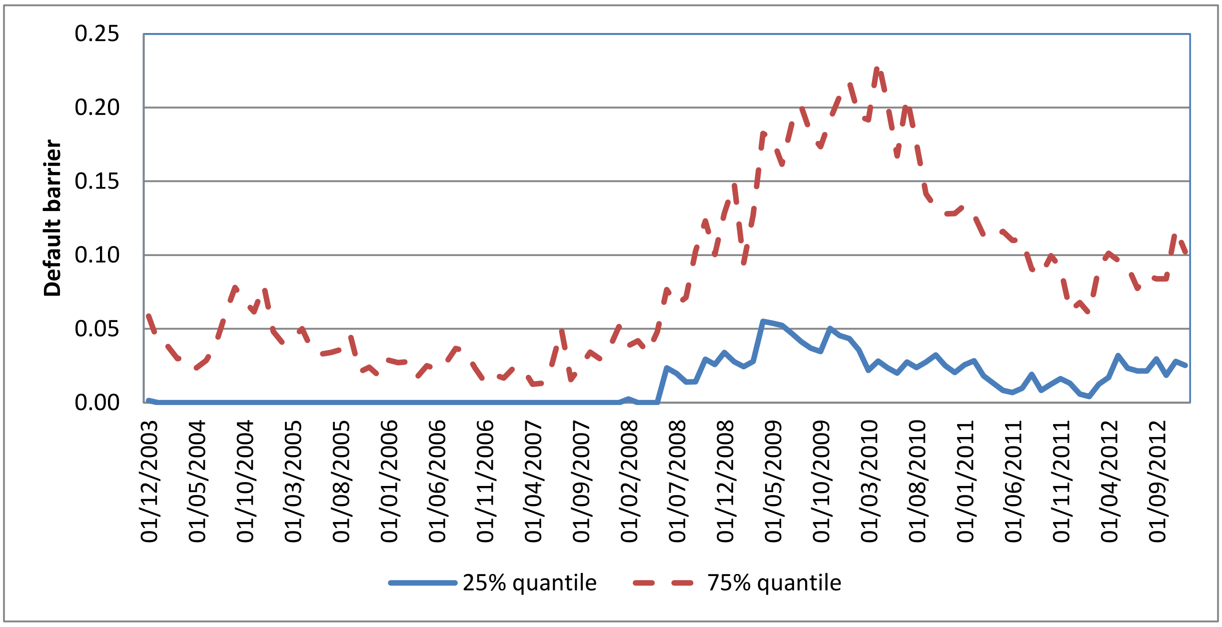

Figure 4. Dispersion of default barriers in Europe. The Figures shows the 75% and 25% quantiles of the distribution of default barriers over the sample period.

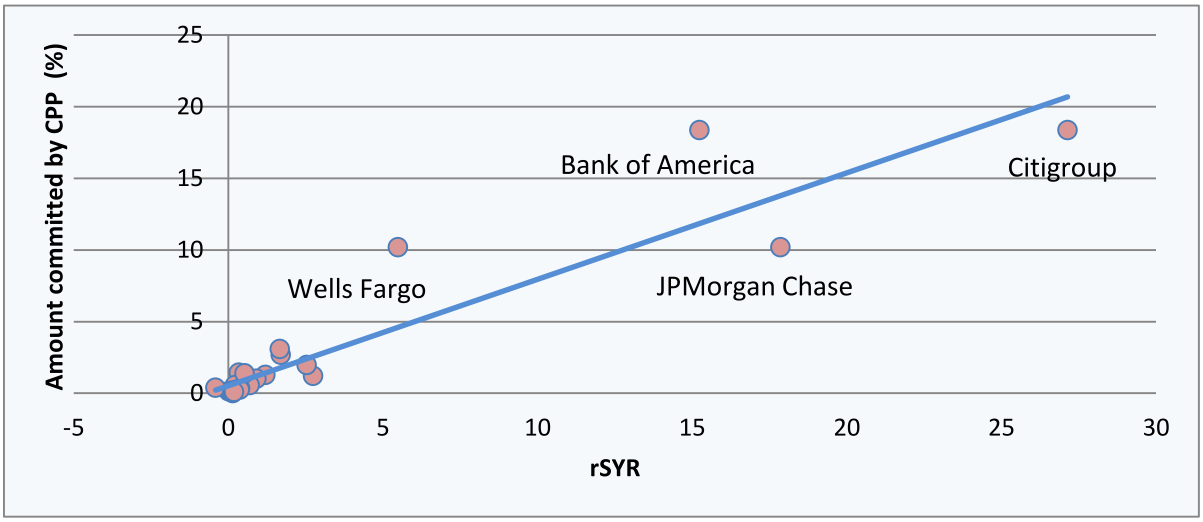

Figure 5. Bank level relationship between government capital injections and systemic risk
Scatterplot of the relative dollar amounts committed by the Capital Purchase Program (CPP) against our measure of bank specific systemic risk (rSYR).

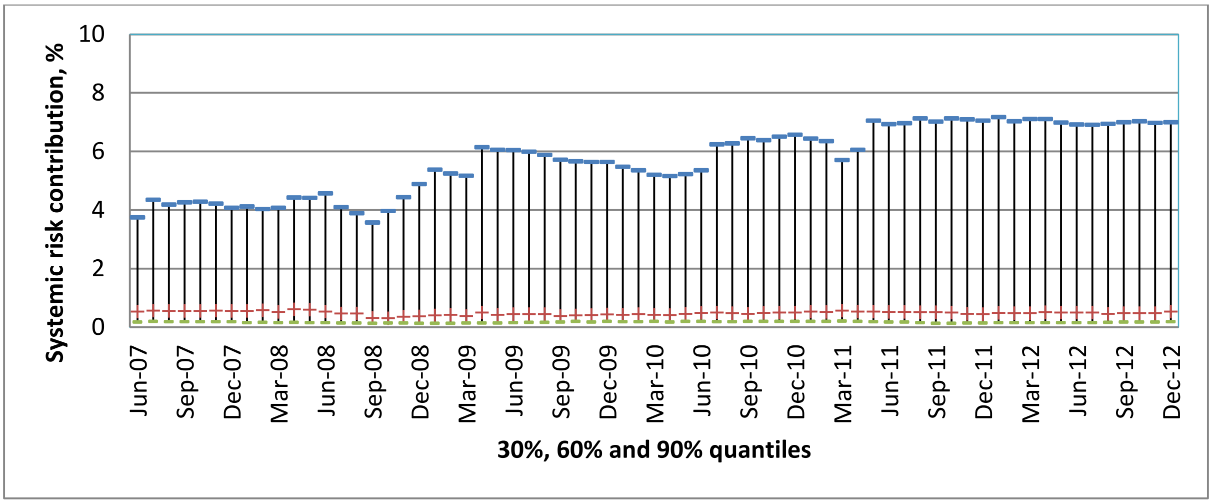

Figure 6. Distribution of systemic risk contributions for US banks. We report 90%, 60% and 30% quantiles over the crisis period.

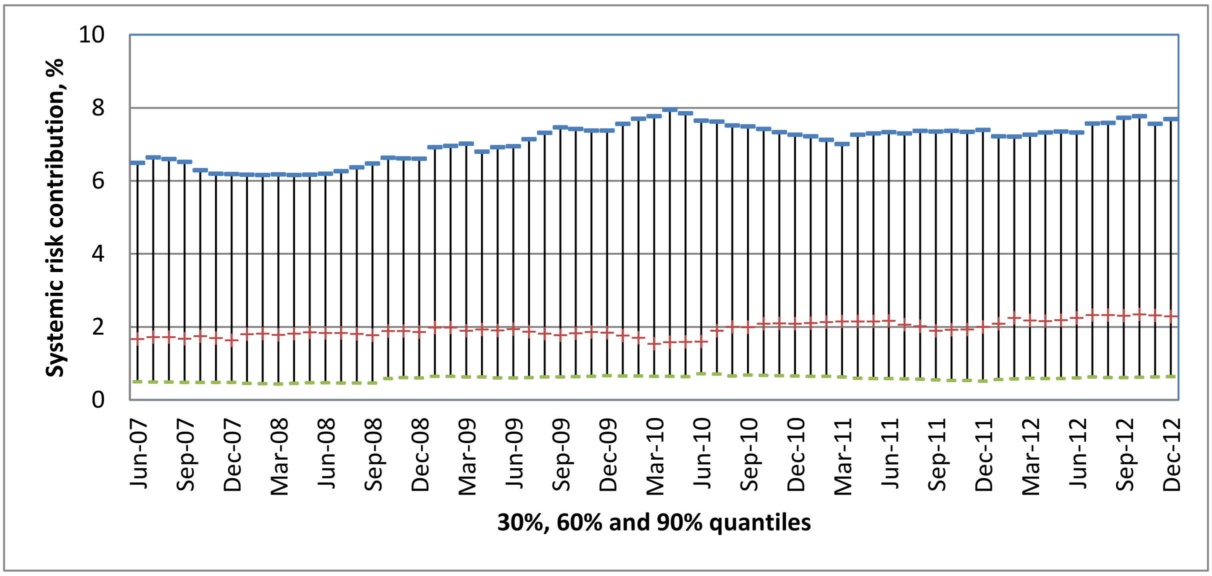

Figure 7. Distribution of systemic risk contributions for European banks. We report 90%, 60% and 30% quantiles over the crisis period.

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				2011 Rankings				
	Asset value Q4 2007 (bn USD)	rSYR	sSYR	AER	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 injections 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 dollar value of the injections divided by the total asset value of the recipient banks 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: proportional capital injection

	Model 1	Model 2	Model 3	Model 4
Constant	0.539**	0.073	2.580***	6.786**
$rSYR_{t-1}$	0.739***	-0.286		
$sSYR_{t-1}$			-0.003	0.007
Total $Assets_{t-1}$		0.012***		0.000
Assets $Growth_{t-1}$		-0.279		-0.200
Assets $Growth^2_{t-1}$		0.019		0.017**
Tier 1 $Ratio_{t-1}$		-0.115		-0.298**
$Leverage_{t-1}$		0.086		-0.052
$Liquidity_{t-1}$		-0.040		-0.025
Return on $Assets_{t-1}$		0.503		0.532
Deposit $Ratio_{t-1}$		0.014		-0.019
Adjusted R-squared	0.849	0.910	-0.028	0.077
Observations	30	30	30	30

Table 3. 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 3 - 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 4. 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. Fixed effects include both cross-section and time effects. *** and ** denote significance at the 1% and 5% level. t-values have been computed with panel robust standard errors.

Panel A: United States

Dependent variable: sSYR

Constant	16.15***	60.25***	78.03***	39.00***	53.43***	65.02***	88.41***	20.74**	-22.22
$Size_{t-1}$	4.26***							3.38***	7.90**
Assets $growth_{t-1}$		-1.77***						-1.33***	-1.20***
Assets $growth^2_{t-1}$		0.37***						0.24***	0.21***
Tier1 $ratio_{t-1}$			-1.56***					-1.72***	-1.65***
$Leverage_{t-1}$				2.01***				1.25***	1.63***
$Liquidity_{t-1}$					0.38***			0.27***	0.08
Return on $assets_{t-1}$						-3.58***		-3.37***	-4.77***
Deposit $ratio_{t-1}$							-0.39***	0.04	-0.03
Fixed effects	No	No	No	No	No	No	No	No	Yes
Adjusted R-squared	0.052	0.034	0.015	0.039	0.032	0.013	0.029	0.134	0.327
Observations	1486	1486	1486	1486	1486	1486	1486	1486	1486

Table 4 - continued

Panel B: Europe
Dependent variable: sSYR

Constant	36.24**	83.52***	87.26***	69.75***	78.06***	87.53***	96.07***	59.23**	95.17***
$Size_{t-1}$	3.80***							2.32***	-0.04
Assets $growth_{t-1}$		-0.41***						0.03	-0.03
Assets $growth^2_{t-1}$		0.05***						0.004	0.01
Tier1 $ratio_{t-1}$			-0.35**					-0.96***	-1.47***
$Leverage_{t-1}$				0.55***				0.37***	0.17***
$Liquidity_{t-1}$					0.18***			-0.02	0.03
Return on $assets_{t-1}$						-7.98***		-4.66***	-2.26**
Deposit $ratio_{t-1}$							-0.32***	-0.05	-0.03
Fixed effects	No	No	No	No	No	No	No	No	Yes
Adjusted R-squared	0.130	0.011	0.004	0.238	0.051	0.100	0.100	0.318	0.494
Observations	1272	1272	1272	1272	1272	1272	1272	1272	1272

Table 5. 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. Fixed effects include both cross-section and time effects. ***, ** and * denote significance at the 1%, 5% and 10% level. t-values have been computed with panel robust standard errors.

Dependent variable: sSYR

	Lag of explanatory variables:	
	One Quarter	Half Year
Constant	6.674	6.220
Size	3.557*	5.671***
Assets growth	-0.041	-0.183**
Assets growth^2	0.023**	0.014
Tier1 ratio	-1.663***	-1.798***
Leverage	0.216***	0.177***
Liquidity	-0.078*	-0.062
Return on assets	-3.102**	-1.110
Deposit ratio	0.048	0.016
US*Size	3.877	0.284
US*Assets growth	-1.385***	-0.933***
US*Assets growth^2	0.201***	0.165***
US*Tier1 ratio	0.145	0.127
US*Leverage	1.413***	2.018***
US*Liquidity	0.240	0.160
US*Return on Assets	-0.744	-3.503**
US*Deposit ratio	0.133	0.019
Fixed effects	Yes	Yes
Adjusted R-squared	0.485	0.494
Observations	2566	2473

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