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The systemic risk of European banks during the financial and sovereign debt crises ☆

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European banks became a source of risk to global financial markets during the financial crisis and attention to the European banking sector increased during the sovereign debt crisis. To measure the systemic risk of European banks, we calculate a distress insurance premium (DIP), which integrates the characteristics of bank size, probability of default, and correlation. Based on this measure, the systemic risk of European banks reached its height in late 2011 around €500 billion. We find that this was largely due to sovereign default risk. The DIP methodology is also used to measure the systemic contribution of individual banks. This approach identifies the large systemically important European banks, but Italian and Spanish banks as a group notably increased in systemic importance during the sample period. Bank-specific fundamentals like capital-asset ratios predict the one-year-ahead systemic risk contributions.

1. Introduction

In late 2011, the European financial system appeared to be on the brink of a major crisis. Investors were faced with the possibility of a Greek default while European leaders wrestled with a fiscal situation that had no clear precedent. As contagion fears spread to Italy and Spain, market participants began to consider the worst-case scenarios. One of the greatest concerns was the systemic risk of the European banking system. If a sovereign default were to lead to a failure of a systemically-important European bank, the resulting financial instability could be disastrous. This type of scenario highlights the need for identifying and understanding the contribution of banks to systemic risk in the financial system.

In this paper, we provide a measure of systemic risk for a broad range of European banks and examine contributing factors. Our systemic risk measure is a distress insurance premium (DIP), which integrates the characteristics of bank size, probability of failure, and correlation. These components capture the main characteristics of systemic risk (Huang et al., 2009, 2012). Based

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on this measure, we show that European banks posed a significant systemic risk, which reached its peak in November 2011. At that point in the unfolding of the European sovereign debt crisis, the problems faced by the European banking system and the potential for global spillovers were clearly the main focus of all market participants and bank regulators.

Our analysis builds on the recent literature attempting to measure systemic risk using publicly available information (see, e.g., Adrian and Brunnermeier, 2014; Acharya et al., 2010; Brownlees, 2012).[4] We empirically measure the hypothetical insurance premium to cover distressed losses in the European banking system based on the inputs of total balance-sheet liabilities, credit default swap (CDS) spreads, and equity return correlations.

After developing this measure of systemic risk, we explore the determinants of systemic risk as well as the contributions from individual banks and countries. The ultimate goal is to understand the sources of systemic risk. The main findings provide a number of insights into the nature of European banks' systemic risk and the policy implications.

First, the systemic risk indicator for European banks is elevated in both the financial crisis and sovereign debt crisis, but the determinants of systemic risk during these periods appear to differ. In 2008 and 2009, the movement in the indicator for European banks reflects spillovers from the U.S. financial crisis. All banks across the region felt the stress produced by the failure of Lehman Brothers in 2008. During this stage of the global financial crisis, market perception of the systemic risk of European banks appears to have been mainly driven by the risk premium component. This suggests that the stress was mostly due to heightened risk aversion and liquidity hoarding in global financial markets.

The elevated systemic risk of European banks during the sovereign debt crisis—reaching its height in 2011—was largely due to increased default risk. Systemic risk quickly increased with the Greek bailout agreement in May 2010 and, as the European sovereign debt crisis unraveled, the systemic risk of European banks rapidly rose to its highest peak in November 2011. Physical default probabilities of European banks rose substantially in the second half of 2011, which points to real solvency risk as a major contributor to systemic risk. This suggests that European banks were faced with real solvency threats from their balance sheets, likely due to their holdings of peripheral European sovereign debt. Systemic risk only began to decline at the end of 2011, which may be attributable to additional liquidity injections from the European Central Bank (ECB).

However, there was another huge run-up in the systemic risk measure in the second quarter of 2012, concerning potential default of a major European country—Spain. Ultimately, a sustained decline of European banking systemic risk only occurred

The macro-prudential perspective was first proposed by Crockett (2000) and Borio (2003). In particular, macroprudential features of the new Basel III accord include additional capital surcharges on systemically-important financial institutions (SIFIs), which is in sharp contrast with the microprudential features of the old Basel I and Basel II accords. Our findings on individual banks' contributions to systemic risk may shed light on the issue of a SIFI capital surcharge for banks around the world.

The remainder of the paper is organized as follows. Section 2 outlines the methodology. Section 3 introduces the data for the major banks in the European banking system along with some descriptive statistics. Section 4 presents empirical results and the final section concludes.

2. Methodology

A consistent framework for systemic risk analysis, as suggested by Borio (2011), should integrate both a time-series aspect of well-defined aggregate systemic risk and a cross-section aspect of proper decomposition into each institution's marginal contribution. Our methodology aims to address three important issues. First, the systemic risk indicator measures the risk for a portfolio of heterogeneous banks; second, how to decompose the systemic risk measure into different components relating to risk factors and economic sources; third, the methodology offers an assessment of the contribution of each bank or each group of banks to the systemic risk indicator.

2.1. Constructing the systemic risk indicator

Although there is no unified definition of financial systemic risk (Borio, 2011; Bisias et al., 2012), an operational systemic risk measure can be constructed as a hypothetical insurance premium against catastrophic losses in a banking system (Huang et al., 2009). To construct this premium, we followed the structural approach of Vasicek (1991) for pricing portfolio credit risk, which is also consistent with the Merton (1974) model of individual firm's default risk. The two key default risk factors, the probability of default (PD) of individual banks and the asset return correlations among banks, are estimated from credit default swap (CDS) spreads and stock return co-movements, respectively.

The one-year *risk-neutral* PDs ($PD_{1,t}$) of individual banks are derived from spreads on five-year CDS contracts, s_t.[6] According to the simplified no-arbitrage condition in Duffie (1999) and Tarashev and Zhu (2008), the discounted expected quarterly CDS premiums must equal the discounted expected loss-given-default:

$$0.25s_t\sum_{k=1}^{4T}\exp[-(h_{t+0.25k}+r_{t+0.25k})(0.25k)]$$
$$=LGD_t\int_t^{t+T}h_\tau\exp[-(r_\tau+h_\tau)(\tau-t)]d\tau \quad (1)$$
$$PD_{1,t}=1-\exp(-h_t) \quad (2)$$

where LGD_t is the loss-given-default, r_t is the risk-free rate and $h_t$is the default hazard rate. It is important to point out that the PD implied from a CDS spread is a *risk-neutral* measure, i.e., it reflects not only the physical (or actual) default probability but also a risk premium component as well. The risk premium component can be the default risk premium that compensates for uncertain cash flow, a liquidity premium that tends to escalate during a crisis period, or an indirect sovereign default component as in the case of European countries like Greece, Spain, and Italy.[7]

We estimate asset return correlations among banks using equity return correlations, following Hull and White (2004). Information from the equity market is well-suited for this purpose, because the market is highly liquid and can incorporate new information on the relationship between banks more quickly than accounting data on bank assets. Equity and asset correlations are equivalent when the leverage ratio is constant, so equity correlations are a reasonable approximation for asset correlations over a short horizon (Huang et al., 2009). For our analysis, the hypothetical insurance contract for the DIP measure covers the default horizon of one quarter.

To ensure the internal consistency of the correlation estimates, we estimate a factor model (Vasicek, 1991; Gordy, 2003) based on the raw pair-wise correlations. In particular, we assume that the asset return of bank i at time $t, \Delta\log(A_{i,t})$, is driven by C common factors, $M_t=[M_{1,t},\ldots,M_{C,t}]'$, and an idiosyncratic factor, $Z_{i,t}$:

$$\Delta\log(A_{i,t})=B_iM_t+\sqrt{1-B_iB_i'}\cdot Z_{i,t}, \quad (3)$$

where $B_i=[\beta_{i,1},\ldots,\beta_{i,C}]$ is the vector of common factor loading coefficients for bank i (with $i=1,\cdots,N$), $\beta_{i,c}\in[-1,1]$ and $\sum_{c=1}^{C}\beta_{i,c}^2\leqslant 1$.[8] The loading coefficients $B=[B_1;\ldots;B_N]$ are estimated using the efficient algorithm proposed by Andersen et al. (2003) to solve the following minimization problem:

$$\min\ tr(\Sigma-BB'-F)(\Sigma-BB'-F)' \quad (4)$$
$$\text{s.t. } diag(F)=I-diag(BB'), \quad (5)$$

where tr is the matrix trace operator (i.e., sum of the diagonal elements), Σ is the raw pair-wise estimate of the correlation matrix, and the diagonal matrix F ensures that the diagonal of the factor-reduced correlation matrix contains only ones.[9] After obtaining the estimated loading coefficients B, we simulate the asset return of bank i at time t, $\Delta\log(A_{i,t})$, according to Eq. (3).

To capture the size effect directly, we use banks' total liabilities in our construction of the systemic risk measure.[10] The amount of banks' total liabilities is clearly important for policy considerations related to perceptions of "too-big-to-fail". First, we use banks' total liabilities as weights for creating an aggregate measure of systemic risk. Second, our "distress insurance premium" (DIP) measures financial distress as the situation in which at least 10% of total liabilities in the banking system go into default. We choose the 10% threshold based on our sample of 58 European banks, because the stress scenario would require the simultaneous failure of at least 2 of the 8 largest institutions.

Based on the inputs of the key credit risk parameters—risk-neutral PDs, correlations, and liability weights—the systemic risk

[6] CDS spreads are considered a purer measure of credit risk than bond or loan spreads (see, Blanco et al., 2005; Forte and Peña, 2009; Norden and Wagner, 2008, among others). Nevertheless, there still may be a liquidity component of CDS spreads that needs to be addressed (see, e.g., Tang and Yan, 2008) We use five-year CDS contracts because they are more liquid than other maturities. The main assumptions needed for Eq. (1) are a flat term structure of risk-free rates and a flat default intensity term structure.

[7] Puzanova and Düllmann (2013) also take the portfolio approach to measure systemic risk, but using the physical probability of default, and assuming constant LGD and correlations.

[8] Without loss of generality, we assume that all the common and idiosyncratic factors are mutually independent and have zero means and unit variances.

[9] In general, four to six common factors can explain up to 95% of the total variation in our correlation sample estimates. Meanwhile, the factor structure can help to increase simulation speed and ensure positive-semidefiniteness of the correlation matrix as an input for the simulation.

[10] This is an important feature of our approach and alternative measures based on value-at-risk (VaR) and expected shortfall (ES) generally do not incorporate this balance-sheet effect directly.

indicator can be calculated by the simulation approach as described in Huang et al. (2009). To compute the indicator, we first construct a hypothetical debt portfolio that consists of total liabilities (deposits, debts and others) of all banks. We then use the simulated asset returns based on Eq. (3) and default thresholds derived from risk-neutral PDs to simulate default scenarios for banks in the portfolio. Let L_i denote the loss of bank i's liability with $i = 1, \ldots, N$, such that $L = \sum_{i=1}^{N} L_i$ is the total loss of the portfolio. The systemic risk of the banking sector, or the distress insurance premium (DIP), is given by the risk-neutral expectation of the loss exceeding a certain threshold level:

$$\mathrm{DIP} = \mathrm{E}^{Q}[L \times 1(L \geqslant L_{\min})], \tag{6}$$

where $L_{\min}$ is a minimum loss threshold or "deductible" value. The DIP formula can be easily implemented with Monte Carlo simulation (Huang et al., 2009).

2.2. Economic composition of systemic risk

In addition to the construction of systemic risk indicator, we also perform several decompositions of the systemic risk into different economic components.

One perspective is to investigate how much of the systemic risk is driven by the movement in physical default risk and how much is driven by the movement in *risk premia*, which includes—but is not limited to—default risk premium and liquidity risk premium. For this purpose, we re-calculate the systemic risk indicator, but using market estimates of the objective or actual default rates rather than the risk-neutral default rates derived from CDS spreads. The corresponding insurance premium against distress losses, on an *actuarial* basis, quantifies the contribution from the expected physical defaults, and the difference between the *market value* (our benchmark result) and the *actuarial* premium quantifies the contribution from risk premia components.

To measure objective or actual PDs, we use expected default frequencies (EDF) reported by Moody's KMV. This measure of PD should more closely move with changes in banks' balance-sheet risk, such as risk of losses on their holdings of mortgage loans or sovereign debt. On the other hand, our benchmark risk-neutral PD input into the systemic risk construct is backed out from market CDS spreads.

Furthermore, we decompose the risk premium component of the systemic risk measure into three components: the default risk premium in the global market is proxied by the difference between corporate 10-year bond yields of BBB rating over AA rating (see, e.g., Chen et al., 2009), the liquidity risk premium is proxied by the spread of European London interbank offered rates, or LIBOR, over the overnight index swap rate, or OIS (see, e.g., Brunnermeier, 2009), and the sovereign risk premium proxied by the spread between Spanish and Italian 10-year sovereign bonds yield and German 10-year Bounds yield. Earlier analysis has shown important differential impacts of default and liquidity risk premium components during different phases of the 2007–2009 global financial crisis (Huang et al., 2012), yet no significant impact of the sovereign risk premium has been documented until the European debt crisis that started in 2010.

When analyzing the default risk of European banks, the response of the sovereign government and/or international institutions to banking distress must be considered. If market participants anticipate a European bank bailout by the its home country or European authority, the risk of the bank's debt will be priced accordingly. Therefore, market prices are not always a good indicator of bank risk when future government intervention is a possibility.

To address this issue, we also estimate banks' risk-neutral PDs from CDS spreads on subordinated debt. Historically, bailouts of European banks have included the bailout of investors in the banks' senior debt, but not the subordinated debt (Moody's Investors Service, 2009). Therefore, CDS spreads on subordinated debt are less subject to the bias of perceived government support. Based on these spreads, we construct an alternative systemic risk indicator that can be compared to the benchmark indicator. Therefore, the difference between the systemic risk measure based on CDS on senior unsecured debt and subordinated debt may provide a crude proxy for market assessment of implicit government support of banks.

2.3. Systemic importance of individual banks

For the purpose of macroprudential regulation, it is important not only to monitor the economy-wide systemic risk, but also to understand each bank's contributions to the aggregate systemic risk. Whereas the macroprudential approach focuses on the risk of the financial system as a whole, regulatory and policy measures are implemented at the level of individual banks. As described below, a proper decomposition allows a systemic risk regulator to easily link the regulatory burden to risk contributions of individual banks (Tarashev et al., 2009a).

Following Kurth and Tasche (2003) and Glasserman (2005), for standard measures of systemic risk including expected shortfall and distress insurance premium, the total value can be properly decomposed into a sum of marginal risk contributions. Each marginal risk contribution is the expected loss from that sub-portfolio, when the full portfolio experiences a large loss. In particular, if we define L as the loss variable for the whole portfolio as earlier, and L_i as the loss variable for a sub-portfolio, the marginal contribution to our systemic risk indicator, the distress insurance premium (DIP), can be characterized by

$$\mathrm{E}^{Q}[L_i \times 1(L \geqslant L_{\min})] \tag{7}$$

The additive property of the decomposition results, i.e., the systemic risk of a portfolio equals the marginal contribution from each sub-portfolio, is important for operational purposes.

One important alternative to our DIP measure is the CoVaR method proposed by Adrian and Brunnermeier (2014). CoVaR looks at the VaR of the portfolio conditional on the VaR of an individual institution, defined as

$$\mathrm{Prob}\left(r_m \leqslant \mathrm{CoVaR}_i^{q,p} | r_i = \mathrm{VaR}_i^p\right) = q$$

where r_i is the market-valued asset return of institution i, and r_m is the return of the portfolio, computed as the average of the r_i's weighted by the lagged market-value assets of the institutions in the portfolio. Adrian and Brunnermeier (2014) proceed to measure institution i's contribution to the systemic risk by ΔCoVaR, defined as

$$\Delta\mathrm{CoVaR}_i^q = \mathrm{CoVaR}_i^{q,q} - \mathrm{CoVaR}_i^{q,0.5}$$

An important concern of CoVaR, or VaR-based measure in general, is that it may not appropriately aggregate the systemic risk contributions of individual institutions.

Another alternative is the MES proposed by Acharya et al. (2010). MES looks at the expected loss of each institution conditional on the whole portfolio performing poorly:

$$\mathrm{MES}_i^q \equiv \mathrm{E}\left(r_i | r_m \leqslant \mathrm{VaR}_m^q\right)$$

where r_i and r_m are the equity returns of institution i and the portfolio.

Brownlees (2012), Acharya et al. (2012) and Engle et al. (2015) propose another systemic risk measure, called SRISK, based on MES. SRISK explicitly takes into account the size of a financial institution. The SRISK for institution i is defined as:

Table 1
European banks: measures of size and default risk.

Group	Countries	Total Equity	Total Liabilites	Average CDS spreads Period 1	Period 2	Period 3	Average EDF Period 1	Period 2	Period 3
1	FR	148.53	4779.28	9.19	83.41	190.24	3.18	22.32	200.20
2	GE	61.30	2958.23	13.33	96.26	164.01	11.69	100.15	413.78
3	GB	254.51	7151.35	8.20	111.23	169.74	4.78	43.81	125.74
4	SZ	47.64	2129.78	5.24	116.82	134.68	2.37	28.76	214.15
5	AS,BE,LX,NE	81.51	2640.94	11.45	137.86	278.57	4.25	36.32	420.51
6	IT,SP	242.23	3470.32	5.98	107.23	320.70	2.37	29.69	142.43
7	GR,IR,PO	48.01	877.08	13.03	290.57	993.40	6.58	62.08	396.35
8	DE,NO,SW	63.50	1575.25	9.01	90.11	126.41	3.80	21.19	63.65
Mean		118.40	3197.78	9.43	129.19	297.22	4.88	43.04	247.10
Median		72.51	2799.58	9.10	109.23	179.99	4.03	33.01	207.17

Note: The table shows measures of size and default risk for eight groups of European banks, labeled by country. Total equity and total liabilities are consolidated amounts as of 2007 in billions of Euros. Average daily CDS spreads and average weekly EDFs during each period are in basis points. "Period 1" is from January 1, 2005 to August 8, 2007; "Period 2" is from August 9, 2007 to May 1, 2010; "Period 3" is from May 2, 2010 to January 26, 2013.

$$\mathrm{SRISK}_i = max[0, E(\text{Capital Shortfall}_i|\text{Systemic Crisis})]$$
$$= max[0, E(k\,\text{Asset}_i - \text{Equity}_i|\text{Systemic Crisis})]$$

where k is the prudential equity/asset ratio. Then institution i's contribution to the aggregate SRISK in percentage is given by

$$\mathrm{SRISK\%}_i = \frac{\mathrm{SRISK}_i}{\sum_{i=1}^{N}\mathrm{SRISK}_i}.$$

There are several differences between DIP and CoVaR, MES or SRISK. First, DIP is a risk-neutral pricing measure derived from both CDS and equity market data, while MES, SRISK and CoVaR are objective distribution-based statistical measures that rely mostly on equity return information. So the latter are pure measures of physical systemic risk, while DIP also contains various risk premium components. Second, DIP, MES and SRISK measure each institution's loss when the system is in distress, while CoVaR measures the system loss conditional on each institution being in distress. Third, MES and SRISK calculate the institution loss when the systemic loss has been realized while DIP is the ex ante loss, taking into account the probability of the systemic risk. So MES and SRISK can be much higher in magnitude than DIP. Fourth, neither CoVaR nor MES incorporates institution size as an *ex ante* input in constructing the systemic risk indicator, while DIP and SRISK do. Approaching systemic risk from different angles, each of the four measures can provide complementary information in the real-time supervisory monitoring of the financial systemic risk.

3. Data summary and descriptive analysis

In July 2011, the European Banking Authority (EBA) released the results of their stress tests for a broad range of 90 European banks, which included large banks from countries around Europe, such as banks from Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom. This group of banks is the starting point of our sample. To the list of banks that participated in the EBA stress test, we add the two large systemically important institutions from Switzerland (UBS and Credit Suisse) and a few others not included in the stress test. Our initial raw sample is composed of close to 100 European banks. We then apply the following data availability criteria for each bank: (i) a minimum number of 200 valid observations of daily CDS spreads since January 1, 2005[11]; (ii) publicly available equity prices since January 1, 2003; and (iii) a minimum number of 20 valid observations of monthly expected default frenquencies (EDF) since January 2005. This results in a final sample of 58 banks.[12]

Our sample data cover the period from January 2001 to January 2013, allowing us to track the evolution of European banks from before the financial crisis through the still evolving sovereign debt crisis. For bank balance sheet information, including total equity and liabilities, we use annual data from Datastream. Market variables, including CDS spreads and EDFs, are used at a higher frequency. We retrieve weekly euro-denominated CDS spreads on 5-year contracts and their recovery rates from Markit. EDFs of individual banks are provided by Moody's KMV. EDF is a market product that estimates expected one-year (physical) default rates of individual firms based on their balance sheet information and equity price data. The method is based on the Merton (1974) framework and explained in detail in Crosbie and Bohn (2002). In this study, we assume that EDFs track closely physical expectations of default. As an alternative measure of default risk, we also use distance-to-default (DTD). See Appendix A for details on all the data that we use in this paper.

Table 1 reports some basic descriptive statistics about the banks in our sample. In this table, we show figures from the banks' balance sheets and market prices according to eight groupings of banks by home country. The first set of columns in Table 1 report the "group" for each bank and the second column lists the home countries in each group.

For the larger European countries including France (FR), Germany (GE), Great Britain (GB) and Switzerland (SZ), the group is the set of banks within a single country (e.g., French banks and German banks). Smaller countries are combined into groups, such as the group for Austria (AS), Belgium (BE), Luxembourg (LX), and the Netherlands (NE) and the group for Denmark (DE), Norway (NO), and Sweden (SW). For the "peripheral" European countries, we combine Italy (IT) and Spain (SP) and also Greece (GR), Ireland (IR) and Portugal (PO). We also use these groupings for some of our later analysis, such as the calculation of within-group correlations.

The summary statistics of total equities, total liabilities, CDS spreads and EDFs in Table 1 provide some context for the subsequent analysis. The Total Equity and Total Liability columns are the sum of the book value equity and liabilities of the banks in each group. As can be seen, these values for the British and the French banks are larger than those of any other European country. The amount of liabilities are particularly important in our measure of

[11] "Valid observations" refers to CDS quotes filtered by Markit, as recommended in the literature (Mayordomo et al., 2014).

[12] The total assets of the 58 banks in our data sample is about 58% of the whole European banking sector asset. Also the frequency for the EDF data gradually increased from monthly to daily for the sample banks over the sample period.

can differ substantially from the *ex post* observations of a handful default events during our sample period. In addition, whereas we allow for time-varying recovery rates, they exhibit only small variation (between 36 and 43%) during the sample period.

The other key credit risk factor, the asset return correlation (lower-right panel), shows small variation over time but large cross-sectional differences. Average correlations were below 40% during the period just prior to the financial crisis and then began to rise above 40% in 2008. Interestingly, average correlations for European banks have been somewhat lower during the sovereign crisis relative to the financial crisis. This may be due to the common response of European banks to U.S. news during the financial crisis, compared to the heterogeneous response to news coming from specific European countries during the sovereign crisis.

Fig. 2 shows the correlation estimates for pairwise correlations and within-group correlations. The equity correlation data begin one year prior to our main sample so that correlations can be calculated over a rolling one-year window. The upper panel plots the averages of pairwise correlations (based on equity return movements) for three categories: for any two banks from the sample (All), for any two banks from the same group (Within), and for any two banks from different groups (Cross). The higher dashed line shows that banks from the same country typically have much higher pairwise correlations than those from different countries. Over time, the pairwise correlations can be as low as 20% and as high as 60%. These differences in pairwise correlations point to the potential bias if the correlation matrix is assumed to be homogeneous.[13]

The lower panel of Fig. 2 plots the within-group average correlations for each of the 8 groups studied in this paper. During the sovereign crisis, the within-group correlations appear to be highest for Swiss banks as well as the Italian and Spanish banks. In contrast, the German banks have a very low within-group correlation, consistent with the more limited concerns about the German banks.

Table 2 also indicates that the key credit risk factors tend to comove with each other.[14] Not surprisingly, risk-neutral and physical PD measures are highly correlated, suggesting that the underlying credit quality of a bank has an important impact on the credit protection cost. PDs and correlations are also positively correlated, confirming the conventional view that when systemic risk is higher, not only the default risks of individual firms increase but they also tend to move together. Lastly, there is a slightly negative relationship between PDs and recovery rates when computed as the average of bank-specific bivariate correlations. This is consistent with the findings in Altman and Kishore (1996) that recovery rates tend to be lower when credit condition deteriorates (procyclical). Recovery rates also tend to have a negative correlation with the other factors when computed as an average bank-specific correlation.

Table 2
Relationship between key credit risk factors.

Variables	CDS	PD	EDF	COR	REC
CDS	1	1.00/1.00	0.83/0.66	0.28/0.22	0.31/−0.04
PD		1	0.82/0.66	0.29/0.23	0.30/−0.05
EDF			1	0.16/0.04	0.56/−0.12
COR				1	−0.27/−0.04
REC					1

Note: The table summarizes the relationship between key credit risk factors: CDS spreads (CDS), risk-neutral probabilities of default (PD), expected default frequencies (EDF), asset return correlations (COR) and recovery rates (REC). In each cell, the first number reports the correlation coefficient between the two time series of the cross-sectional averages of the corresponding row and column factors, and the second number reports the average of the bank-specific correlation coefficient between the two factors.

consider the magnitude and determinants of systemic risk, including the role of the risk premium, and then identify the contribution of individual banks to the aggregate indicator of systemic risk and relate these systemic importance of individual banks to their firm-specific economic fundamentals.

4.1. The magnitude and determinants of systemic risk

Figs. 3 and 4 show the magnitude of the systemic risk indicator for the European banking system from 2006 through early 2013. Fig. 3 plots the systemic risk of European banks during the financial crisis, including major dates during the financial crisis such as the freezing of BNP Paribas funds and the failure of Lehman brothers. Fig. 4 plots the systemic risk of European banks during the sovereign debt crisis, with a number of dates beginning with the Greek government's acceptance of the €110 billion EU-IMF support package on May 2, 2010. As explained in the methodology, our systemic risk indicator can be interpreted as a "distress insurance premium", in which financial distress is defined as the situation in which at least 10% of total liabilities in the banking system go into default or at least two out of the largest eight banks default simultaneously. In both figures, this insurance cost is represented as the premium rate (unit price in percentages) on the left axis and in Euro amount (€ billions) on the right axis.

As shown in Fig. 3, the systemic risk indicator for European banks was very low at the beginning of the global financial crisis. For a long period before BNP Paribas froze three funds due to the subprime problem on August 9, 2007, the aggregate distress insurance premium for the list of 58 European banks was merely several

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basis points (or less than €10 billion). The indicator then moved up significantly, reaching the first major peak when Bear Stearns was acquired by JP Morgan on March 16, 2008. The situation then improved significantly in April-May 2008 owing to strong intervention by major central banks.[15] Things worsened dramatically in September 2008 with the failure of Lehman Brothers. Market panic and increasing risk aversion pushed up the price of insurance against distress in the banking sector, and European banks were not spared. The crisis also hit the real sector, both in the United States and Europe: unemployment went up and forecasts of economic growth were substantially revised downward. The distress insurance premium for European banks hiked up and hovered in the range of 100 basis points (or €240 billion). The situation didn't improve until late March 2009. In particular, the adoption of unconventional policies, the announcement of a round of stress tests of systemic banks—first in the United States and then in Europe—and strengthened cross-border coordination among policy institutions helped calm the market.

Fig. 4 shows the dramatic increase in the systemic risk indicator for European banks during the sovereign debt crisis. Although the indicator had fallen to relatively low levels by the end of 2009, as markets began to stabilize following the global financial crisis, the indicator jumped up in May of 2010 when Greece signed a bailout agreement with the EU and IMF. This appears to have been somewhat of a "new norm" through mid-2011, but, at this point, the crisis reached a new stage. In the summer of 2011, markets began to have significant concerns about the contagion of a Greek default spreading to other European countries. Italy and Spain appeared to be possible dominoes in the next stage of the sovereign crisis. French banks began to show signs of liquidity strains due to their exposure to the sovereign debt of these countries and the withdrawal of funds by U.S. money market mutual funds. As the fears grew, European leaders attempted to halt the downward spiral by issuing greater commitments to financial firewalls, such as expansions to the European Financial Stability Fund (EFSF). Ultimately, our systemic risk indicator reached its peak in November 2011. This appears to be the heart of the sovereign debt crisis, just before the ECB expanded its liquidity provision through a dollar-swap line with the U.S. Federal Reserve and the first of its 3-year Long-Term Refinancing Operations (LTRO) for European banks. There was another run-up in the systemic risk measure in the second quarter of 2012, concerning potential default of Spain. Ultimately, the sustained decline of the European banking systemic risk only occurred after Mario Draghi's "courageous leap" and "whatever it takes" speeches around June and July, followed by ECB's nonconventional Outright Monetary Transactions (OMT) program launched in August 2012.

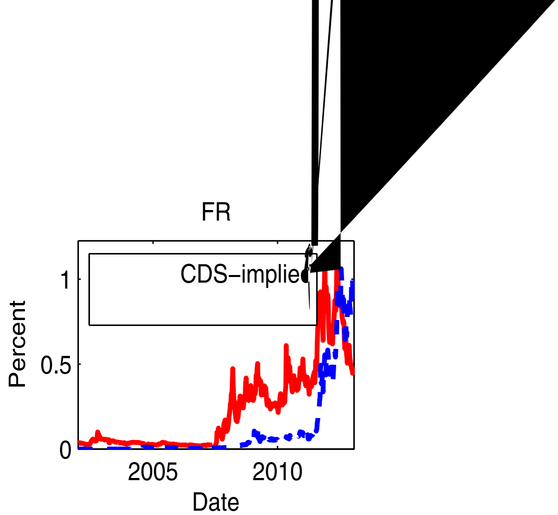
As can be seen by comparing Figs. 3 and 4, the systemic risk of European banks reached its highest level in late 2011 during the sovereign debt crisis. At that time, the financial distress insurance cost reached around €500 billion. This points to the severity of the situation facing European leaders as they attempted to defuse the potential disaster of the Greek debt situation.

One challenge in using CDS spreads to estimate PDs is that CDS spreads may reflect perceptions about the likelihood of government intervention. If market participants expect a bank to be bailed out, they will reduce the price of insuring the bank's debt against default. As a first step to address this possible bias, we have also computed the risk-neutral PDs using CDS spreads on banks' subordinated debt. Subordinated debt holders are less likely to be paid off in a bank bailout, so the CDS spreads should be less influenced by implicit government support.

Fig. 5 shows the systemic risk measure based on subordinated debt, with the indicator based on senior debt provided for comparison. As expected, the subordinated debt indicator is higher than the senior debt indicator, which points to greater levels of systemic risk apart from government support. It should be noted that government support reduces the likelihood of bank default, which reduces banks' systemic risk, but during a fiscal crisis this is not the end of the story. Part of the systemic risk posed by the European banking system during the sovereign debt crisis was this very issue. If the sovereign governments were forced to bail out their banks, this would greatly increase their fiscal burden, which would then feedback into the concerns about the sustainability of their sovereign funding.

Table 3 examines the determinants of the systemic risk indicator. The level of risk-neutral PDs is a dominant factor in determining the systemic risk, explaining alone 93% of the variation in the systemic risk indicator (Regression 1). On average, a one-percentage-point increase in average PD raises the systemic risk indicator by 17 basis points. The level of correlation also matters, but to a lesser degree and its impact is largely dissipated once PD is included. This is perhaps due to the strong relationship between PD and correlation for the sample banking group during this special time period. In addition, the recovery rate has the expected negative sign in the multivariate regressions, as higher recovery rates reduce the ultimate losses for a given default scenario.

Interestingly, the heterogeneity in PDs across banks has an additional role in explaining the movement in the systemic risk



indicator (as shown in the bottom of Table 3). The dispersion in PDs across the 58 banks has a significantly negative effect on the systemic risk indicator.[16] This partly supports our view that incorporating heterogeneity in PDs is important in measuring the system risk indicator. It also suggests that greater dispersion of PDs tends to lower the probability of default clustering and by extension reduce the cost of protection against distressed losses. This has interesting implications for models of systemic risk based on the number of banks failing rather than the size of banks that fail, as in "too many to fail" (Acharya, 2009).

The results have two important implications for bank supervisors. First, given the predominant role of average PDs in determining systemic risk, a first-order approximation of the systemic risk indicator would be the weighted average of PDs (or CDS spreads). This is consistent with Rodŕguez-Moreno and Peña (2013), who find that the first principal component of banks' CDS spreads outperforms several other market-based measures of systemic risk. The large role of PDs suggests that microprudential supervision, which focuses on PD, is an important input into macroprudential supervision. Second, the average PD is a decent approximation but it is not sufficient in reflecting the changes in the systemic risk. Correlations and heterogeneity in PDs also matter, as emphasized in a macroprudential perspective.

4.2. The role of risk premium

This part of the analysis builds on the upper panels in Fig. 1 that provide an initial perspective on the aggregate trends in two difference measures of default likelihood for European banks. The probabilities of default (PDs) implied by CDS spreads are a risk-neutral measure and include not only the expected risk of default, but also the risk premium. In contrast, the PDs estimated by Moody's KMV–EDF are the market estimates of physical (or actual) PDs. Here, we explore the differences in these measures and the implications for our measure of systemic risk.

Fig. 6 shows the discrepancies between the two measures of probability of default for the banks within each group (based on home country). Each of the eight panels provides a comparison of the risk-neutral PDs implied by CDS spreads with the physical PDs measured by EDFs. As can be seen, the significant increase in risk-neutral PDs in October 2008 was primarily driven by the

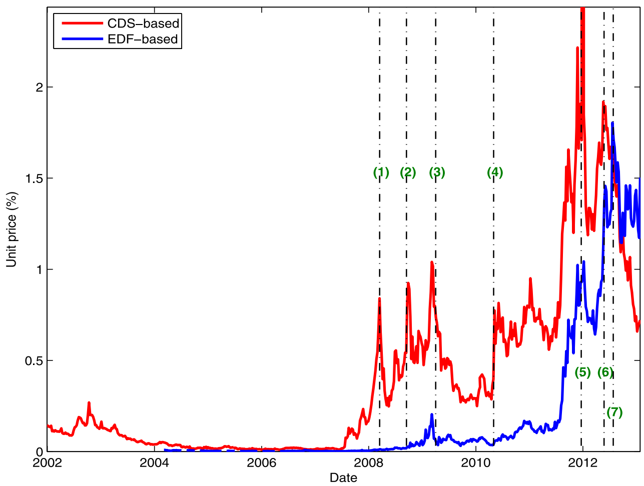


Fig. 7. Comparing systemic risk indicators based on CDS and EDF. Note: The figure compares the values of the systemic risk indicators for the European banking sector based on CDS and EDF information. Systemic risk is measured as the unit price for insuring against financial distress (at least 10% of total liabilities in the banking system in default). Senior debt information is incorporated in both measures. The events corresponding to the labels in the figure are as follows: (1) March 16, 2008: Bear Stearns was acquired. (2) September 15, 2008: Lehman Brothers failed. (3) April 2, 2009: G20 Summit. (4) May 2, 2010: Greek government accepted €110 billion EU-IMF support package. (5) December 21, 2011: The first 3-year LTRO was conducted. (6) May 24, 2012: Mario Draghi's "courageous leap" speech. (7) July 26, 2012: Mario Draghi's "whatever it takes" speech.

heightened risk premium component of the global financial crisis. In other words, the average risk-neutral PDs increased significantly, but physical PDs did not increase nearly as much. The difference is explained by an increased risk premium.

In 2011, both PD measures increased sharply, reflecting the fact that the European sovereign debt crisis placed the European banks in a full-fledged economic crisis. The sovereign debt crisis is a crisis of European origin, so the physical probability of default of European banks is much greater during this period relative to the global financial crisis. While the loss of confidence remained as the main concern in financial markets, the deterioration in Europe's real economy imposed heavy pressure on the banking system.

The failure probability based on EDFs increased most remarkably in 2011 for banks in core European countries, such as France and Germany. In contrast, the systemic risk for Italian and Spanish banks appears to have been driven primarily by the risk premium. These results suggest that some core European banks may have had higher CDS premiums due to physical risk of default (e.g., French banks), whereas some peripheral banks were pressured by investors due to a shift in market sentiment (e.g., Italian banks).

If we use the physical PD measure (EDF) as the input, we can calculate an alternative systemic risk indicator which assumes that all risk premium components are zeros. In other words, the new indicator reflects an insurance premium on an *actuarial* basis, without compensation for bearing the uncertainty in payoff. Fig. 7 plots the EDF-based systemic indicator for the full sample period, along with the benchmark CDS-based indicator for comparison. Similar to the pattern in PDs, the elevated systemic risk of European banks in 2008 is driven primarily by a rising risk premium. Since the second half of 2011, both the risk premium and physical default risk rose substantially as Europe's sovereign debt crisis turned into a real economic recession. Based on the rapid increase of the EDF-based indicator in 2011, it appears that physical default risk was a greater contributor to the systemic risk of European banks during the sovereign debt crisis.

The levels and trends of the benchmark and EDF-based indicators differ in other interesting ways. First, the EDF-based indicator is lower, which provides strong evidence of the resilience of European banks during the crisis. In the worst period (late 2011), the EDF-based indicator hovered below 105 basis points (or €270 billion), which represented only a fraction of the CDS-based indicator. This suggests that, during a crisis period, the bailout cost of a market-based solution tends to be larger than that justified by an objective assessment of the default losses, because of risk aversion and reduced liquidity. Second, CDS spreads (main drivers of risk premium) typically lead bank equity prices (main drivers of EDFs) at the early stages of the crisis. The EDF-based indicator shows that systemic risk did not deteriorate until the summer of 2011. This provides a different picture from the benchmark case using the risk-neutral PDs, which began increasing in 2010.[17]

It has been argued that the risk premium could be the main component of CDS spreads during a crisis (see, e.g., Kim et al., 2009). Given that the benchmark systemic risk indicator is based on risk-neutral measures, we can assess how much of its movement is driven by market sentiments (change in attitudes toward default risk and liquidity risk) and how much is attributable to the change in the "pure" credit quality (or actual potential default loss) of the banks.

We run a regression analysis that examines the impact of physical default rates and risk premium factors on the CDS-based systemic risk indicator. In Table 4, physical default risk (or objective default rates) is proxied by average distance-to-default (DTD) of sample banks, the corporate default risk premium in the European market is proxied by the difference between BBB- and AA-rated corporate 10-year bond yields (see Chen et al., 2009), the liquidity risk premium in the global market is proxied by the European LIBOR-OIS spread (see Brunnermeier, 2009), and the sovereign risk premium, as we propose, is measured by the spread between Spanish and Italian 10-year sovereign bond yields and 10-year German Bunds.[18] We choose DTD, instead of EDF, to proxy physical default risk in this regression analysis, because DTD reveals the pure information from the current stock market. EDF uses DTD as the major input, but it also relies on a mapping based on historical default events to translate DTD to default probabilities.

As shown in the table, the sovereign risk premium explains most of the variation in the systemic risk indicator. In univariate regressions, sovereign risk premium explains 91% of the total systemic risk variation, much higher than credit risk premium (13%) and liquidity risk premium (19%) and even higher than the DTD—physical default risk (60%). Furthermore, in the multivariate joint regression, the total explaining power increases to 94% with the default risk premium being driven to be statistically insignificant.

Fig. 8 plots the contribution effect of physical default risk, default risk premium, liquidity risk premium, and sovereign risk premium, according to Regression 5 in Table 4. As can be seen, the liquidity risk premium was the significant contributor to the systemic risk of European banks during the financial crisis, especially in late 2008. Its contribution also rose in late 2011. The two surges in its contribution match the two peaks of the DIP measure. This observation is consistent with the liquidity dry-up feature of the recent crisis, and reflects the associated market concerns.

However, for the sovereign debt crisis in 2010 and 2011, the primary contributor has been the sovereign risk premium. The

[17] Indeed, the decoupling between CDS-implied PDs and EDFs is a phenomenon that characterizes not only European banks, but also the U.S. banks studied in Huang et al. (2012).

[18] Alternatives to our sovereign risk proxy (as suggested by a referee) include European sovereign CDS indexes, such as DSEV5E. The results using alternative proxies are reported in Tables 1 and 2 of the online appendix.

increase in the spread between Spanish and Italian sovereign bond yields and German yields has been the main driver in the run-up in systemic risk for European banks, especially in late 2011 and the summer of 2012. This shows that our measure of systemic risk as a distress insurance premium is relatively successful at capturing the main risk to bank solvency during the sovereign debt crisis.

In comparison, the contribution from the physical stress, DTD, to DIP remained significant throughout our sample, and steadily increased from financial crisis to sovereign debt crisis, showing that prolonged financial crisis weakened the economic fundamental, making physical stress more prominent.

Lastly, as insignificant in the multivariate joint regression in Table 4, the default risk premium (Bbb-Aa) does not show up visibly in Fig. 8. The insignificance is perhaps due to the strong European government intervention during the recent financial crisis, so that the market is not overly concerned about charging a premium for the default risk.

4.3. The contributions of individual banks to systemic risk

The other natural question is the institutional sources of vulnerabilities, i.e., which banks are systemically more important or contribute the most to the increased vulnerability? Using the methodology described in Section 2, we are able to provide an answer to this question.

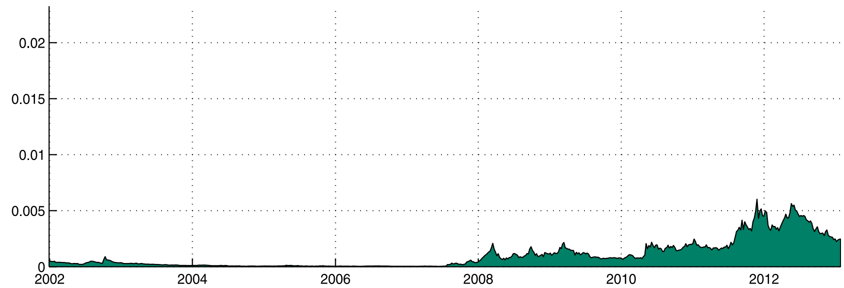
We first calculate the marginal contributions of each group of

Table 5
Marginal contribution to systemic risk by bank on specific dates.

Bank name	Country	Group	Marginal contribution by bank					Bank equity in 2011 (-2007)
			08/09/2007	03/07/2009	05/02/2010	11/26/2011	01/24/2013	
ACA	FR	1	1.405	15.100	18.818	50.132	22.977	42.80 (2.11)
BNP	FR	1	2.420	19.499	20.772	57.747	20.482	75.37 (21.57)
CC	FR	1	0.006	0.360	0.246	1.044	0.205	9.23 (0.75)
KN	FR	1	0.415	5.011	1.296	10.496	4.758	16.87 (

contribution of German and U.K. banks decreased substantially. This corresponded to a relative increase in the contributions of other European countries.

The systemic risk contribution of some of the European countries changed substantially between the financial crisis and the sovereign debt crisis. In particular, the systemic risk contribution of Italian and Spanish banks increased the most during the sovereign debt crisis period. While the contribution of German banks remained low, the contribution of U.K. somewhat increased again in the later part of the sample. By country, the largest contributors of banks to the systemic risk are the Italian, Spanish and U.K. banks. It is interesting to note that Spanish and Italian banks were very minor players during the global financial crisis, likely due to their more traditional business models of local



lending and local deposit-taking. In contrast, these banks have now become major players in the unfolding of the sovereign debt crisis. Perhaps due to their local risk concentration and their holdings of sovereign debt, they pose significant systemic risk for the current situation in Europe.

Table 6 examines the determinants of marginal contribution to systemic risk for each bank, using an OLS panel regression on the daily data.[19] The first regression shows that a bank's size (i.e., total liability weight), is the primary factor in determining marginal contributions both in level and in percentage terms. This is not surprising, given the conventional concern about "too-big-to-fail". Interestingly, a bank's probability of default matters, but to a lesser extent than bank size. Table 6 also shows that equity correlations are an important determinant of a European bank's contribution to systemic risk. This supports the claim that correlation should be a factor in determining banks' status as globally systemically-important financial institutions (G-SIFIs). It also supports the view for distinguishing between micro- and macro-prudential perspectives of banking regulation, i.e., the failure of individual banks does not necessarily contribute significantly to the increase in systemic risk. The second regression suggests that there are significant interactive effects. Adding interactive terms between weight and PD or correlation have additional and significant explanatory power, indicating that there is a significantly nonlinear contribution of the three systemic risk inputs—that is, PD, correlation, and size. Overall, the results suggest that the marginal contribution is the highest for large (i.e., high-weight) banks which observe increases in PDs or correlations.

The effects documented in Table 6 are clearer in a hypothetical calibration exercise examining the overall relationship between a bank's systemic risk and the institution's size, PD, and average correlation, as shown in Fig. 10.[20] The figure shows that systemic risk is increasing with bank size, PD, and correlation, but these relationships are nonlinear. For a few relatively large banks, they contribute

Table 7
DIP, SRISK, and ΔCoVaR on two dates.

Bank Name	Country	Group	G-SIFI	March 7, 2009			November 26, 2011		
				DIP	SRISK	ΔCoVaR	DIP	SRISK	ΔCoVaR
BNP	FR	1	1	19.50	171.43	24.31	57.75	163.51	19.16
DBK	GE	2	1	16.66	176.09	26.02	57.23	176.42	26.13
ACA	FR	1	1	15.10	131.01	16.90	50.13	130.46	9.06
RBS	GB	3	1	19.12	217.96	7.80	47.56	145.25	10.74
SAN	SP	6	1	14.43	92.61	23.19	40.08	81.24	21.36
SOCGEN	FR	1	1	8.97	93.26	11.26	39.40	95.82	7.53
UCG	IT	6	1	10.50	87.22	6.75	30.53	73.31	5.13
ING	NE	5	1	12.37	113.66	8.66	27.62	105.60	13.22
HSBC	GB	3	1	17.93	162.60	37.99	24.16	99.75	35.92
LLOY	GB	3	1	24.28	53.51	9.25	22.95	86.70	7.65
ISP	IT	6	0	5.63	58.36	7.06	21.24	54.60	4.62
BBVA	SP	6	0	6.65	47.19	14.22	18.98	36.55	11.99
UBS	SZ	4	1	14.75	116.21	30.11	18.03	81.37	20.58
CBK	GE	2	1	4.87	48.87	1.46	14.45	59.43	3.52
CSG	SZ	4	1	8.27	62.98	17.60	14.04	62.55	13.09
KN	FR	1	1	5.01	44.20	1.53	10.50	35.11	1.60
NORDEA	SW	8	1	4.95	36.69	6.41	10.38	45.05	11.52
DEXIA	BE	5	1	5.02	54.22	4.89	9.44	33.17	1.70
KBC	BE	5	0	2.50	30.41	1.36	7.03	24.68	1.04
BMPS	IT	6	0	1.39	14.19	1.63	6.98	18.93	0.71
DANSKE	DE	8	0	3.79	36.66	1.84	6.14	31.61	3.30
STAN	GB	3	0	3.01	NaN	0.13	4.65	NaN	0.15
POP	SP	6	0	1.85	9.09	1.42	4.63	8.40	1.23
SEB	SW	8	0	2.82	17.97	1.76	4.54	16.75	3.93
EBS	AS	5	0	2.55	16.64	1.05	4.06	16.85	1.08
UBI	IT	6	0	0.81	8.38	1.46	3.43	9.68	0.75
SWED	SW	8	0	2.15	12.37	0.26	3.22	12.86	2.74
SVK	SW	8	0	1.67	15.32	3.45	3.06	15.19	5.45
BSAB	SP	6	0	1.02	4.93	1.38	2.84	5.54	0.93
SNS	NE	5	0	1.62	9.79	0.52	2.74	9.92	0.30
BCP	PO	7	0	0.42	6.23	0.56	2.74	7.55	0.16
ETE	GR	7	0	1.21	6.28	1.07	2.17	8.26	0.38
BKT	SP	6	0	0.34	3.49	1.47	1.81	4.07	0.60
BKIR	IR	7	0	1.34	15.69	0.08	1.68	11.07	0.46
MB	IT	6	0	0.34	3.51	1.21	1.49	5.27	0.80
EFG	GR	7	0	0.75	5.51	0.43	1.35	6.06	0.04
BPI	PO	7	0	0.18	2.85	0.35	1.06	3.38	0.15
CC	FR	1	0	0.36	17.73	0.68	1.04	16.69	0.54
ALPHA	GR	7	0	0.67	4.31	0.32	1.03	4.55	0.05
PMI	IT	6	0	0.24	3.21	0.31	0.80	3.86	0.17
IPM	IR	7	0	0.71	NaN	NaN	0.36	NaN	NaN
PAS	SP	6	0	0.19	1.69	0.16	0.32	1.85	0.13
ESF	LX	5	0	0.33	NaN	NaN	0.28	NaN	NaN
BEB2	GE	2	0	0.18	9.95	1.21	0.18	8.12	1.05
IKB	GE	2	0	0.26	3.44	0.01	0.12	NaN	NaN
VANL	NE	5	0	0.03	NaN	NaN	0.06	NaN	NaN
OVAG	AS	5	0	NaN	NaN	NaN	0.04	2.02	0.00
CAM	SP	6	0	0.19	5.50	0.01	0.00	5.46	0.00
DNB	NO	8	0	1.65	NaN	1.64	NaN	NaN	NaN
AIB	IR	7	0	1.38	NaN	NaN	NaN	NaN	NaN
DPB	GE	2	0	0.81	18.59	2.41	NaN	NaN	NaN
PEIR	GR	7	0	0.51	4.06	0.30	NaN	NaN	NaN
BIL	IT	6	0	0.25	NaN	NaN	NaN	NaN	NaN
BARC	GB	3	1	NaN	190.54	8.46	NaN	NaN	NaN
HBOS	GB	3	0	NaN	NaN	NaN	NaN	NaN	NaN
BNL	IT	6	0	NaN	NaN	NaN	NaN	NaN	NaN
ANGLO	IR	7	0	NaN	NaN	NaN	NaN	NaN	NaN
DEPFA	IR	7	0	NaN	NaN	NaN	NaN	NaN	NaN

Note: A list of the 58 banks in the sample and their DIP, SRISK, and ΔCoVaR on two dates. All measures are in billions of Euros. The banks are first sorted by their marginal contributions to DIP on November 26, 2011. NaN indicates data is unavailable. The G-SIFI column reports the list of globally systemically-important financial institutions published by the FSB on November 4, 2011.

the bank level.[25] Depending on the specific set of variables included in the estimations, the sample of banks varies between 46 and 55 banks.

As expected, the coefficient on bank size, as measured by log assets, is positive and significant in most specifications. By construction, DIP includes banks' size as one of its components. More importantly, we analyze the effect of banks asset structure on the systemic risk of banks. We use two proxies to capture the composition of assets: Loans/Assets and Liquid assets/Deposits and ST funds, where ST stands for short term. The first measure reflects banks' focus on a more traditional lending business, while the second indicates the liquidity position of the bank. Both measures have negative and significant coefficients in all the specifications that use the one-year-ahead DIP. We interpret this

[25] The start date of this regression sample is determined by the adoption of IFRS accounting standards in the European Union in 2005. The change in accounting standards creates a break in the financial statements of the banks.

result as evidence that more traditional lending-focused banks and banks with more liquid assets are less likely to increase systemic risk.

Next we check whether the banks' capital structure is important in predicting DIP. First, Loans/Deposits measures to what extent loans are financed with deposits, which are deemed to be a more stable source of financing. We find that the coefficient on this measure is positive and significant for the one-year-ahead DIP, implying that banks that finance their lending with non-deposit

Table 8
DIP and bank-specific characteristics.

Dependent variables	Average DIP				Maximum DIP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log assets	0.013	0.012	0.015	0.013	0.023	0.028	0.026	0.027
	(2.816)	(2.225)	(2.600)	(1.693)	(2.369)	(3.110)	(2.609)	(1.935)
Loans/Assets	−0.066	−0.088	0.015	−0.004	−0.079	−0.113	0.103	0.074
	(−2.108)	(−2.487)	(0.839)	(−0.171)	(−1.755)	(−2.228)	(2.396)	(1.567)
Liquid assets/Deposits and ST funds	−0.044	−0.048	−0.035	−0.036	−0.065	−0.074	−0.033	−0.036
	(−2.100)	(−2.141)	(−2.050)	(−1.954)	(−1.997)	(−2.207)	(−1.483)	(−1.513)
Loans/Deposits	0.015	0.023	0.006	0.012	0.021	0.033	−0.003	0.006
	(2.279)	(2.509)	(1.279)	(1.800)	(2.119)	(2.461)	(−0.287)	(0.554)
Equity/Assets	0.233	0.201	0.368	0.326	0.267	0.273	0.603	0.580
	(2.696)	(1.449)	(3.597)	(2.617)	(1.602)	(1.148)	(3.573)	(3.011)
ROA	−0.016	0.173	−0.157	0.044	0.093	0.350	−0.307	−0.081
	(−0.131)	(0.857)	(−1.340)	(0.263)	(0.461)	(1.142)	(−1.544)	(−0.302)
Market to book ratio	−0.005	−0.003	0.001	0.002	−0.008	−0.004	0.006	0.008
	(−2.429)	(−1.714)	(0.505)	(1.295)	(−2.457)	(−1.310)	(2.400)	(2.327)
Government support		0.003		0.003		0.005		0.004
		(1.832)		(2.558)		(2.144)		(2.798)
Constant	−0.117	−0.114	−0.194	−0.175	−0.222	−0.296	−0.384	−0.392
	(−1.952)	(−1.467)	(−2.644)	(−1.735)	(−1.770)	(−2.392)	(−3.089)	(−2.278)

The global financial crisis and the European sovereign debt crisis have caused policymakers to reconsider the institutional framework for overseeing the stability of their financial systems. It has become generally accepted that the traditional microprudential or firm-level approach to financial stability needs to be complemented with a system-wide macroprudential approach. Our results support the claim that large, correlated European banks and some groups of smaller European banks can pose systemic risk and should be subject to greater regulatory standards—a pan-European macroprudential regulation scheme.

Appendix A. Data sources and definitions

Our analysis uses data for the period between January 3, 2001 and January 24, 2013. The list of variables and their sources are as follows:

1. The daily CDS spreads and the associated expected recovery rate for each financial institution are retrieved from Markit. The CDS quotes refer to 5-year contracts denominated in Euros with a "modified-modified" (MM) restructuring clause for both senior unsecured and subordinated debts. We use the last valid observation each week to construct weekly CDS data.
2. The weekly return correlations are calculated from daily equity data, provided by Datastream. We use equity return correlations to proxy asset return correlations, and calculate non-parametric historical correlations based on the past one year of daily arithmetic equity returns.
3. Financial variables.
   (1) Risk-free rate. We use the daily 5-year implied swap rate to measure the risk-free rate. The swap rate is retrieved from Bloomberg.
   (2) Default risk premium. We use the daily BBB-AA spread to proxy the corporate default risk premium. The spread is equal to the yields of ten-year Euro-zone industrials rated BBB minus those rated AA, both of which are retrieved from Bloomberg.
   (3) Liquidity risk premium. We use the daily three-month Euro LIBOR/OIS spread to proxy the liquidity risk premium. The data is retrieved from Bloomberg.
   (4) Sovereign risk premium. We use the daily difference between Germany 10-year generic yield and the average of Spanish and Italian 10 year generic yields weighted by their quarterly GDP's, to proxy the peripheral European sovereign risk premium. All the sovereign yields are retrieved from Bloomberg.
4. Banks' balance sheet information, i.e., annual information of total assets and total liabilities for the banks in our sample, is available from Datastream.
5. The expected default frequency (EDF) data is provided by Moody's KMV. We use the 1-year horizon for EDF, and the data frequency gradually increased from monthly to daily in 2006.
6. The monthly distance-to-default (DTD) data is available on the web site of the Risk Management Institute at National University of Singapore.
7. The daily SRISK and CoVaR in million US dollars are kindly provided to us by Clara Vega. We translate them into million Euros by the Euro/USD exchange rates from Bloomberg. Rob Capellini at NYU V-Lab also provided us with similar data and helpful insights on SRISK.

Appendix B. Supplementary tables and figures

Supplementary tables and figures associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2015.09.007.

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