How Much of Bank Credit Risk Is Sovereign Risk? Evidence from the Eurozone*

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October 2014

Abstract

We model the term structures of sovereign and bank credit default swaps by using a multivariate credit risk model. First, the probability of joint defaults of large Eurozone sovereigns (systemic risk) is separated from that of sovereign-specific defaults (country risk). Then, individual banks' exposures to each type of sovereign risk, as well as bank-specific credit risk, are quantified. Banks' exposures to each type of sovereign risk vary with their size, holdings of sovereign debt, and expected government support. On average, 45% of French and Spanish banks', but only 30% of Italian and 23% of German banks' credit risk is sovereign risk. Furthermore, short- to medium-term contracts are particularly informative on sovereign systemic risk.

Keywords: Sovereign and bank credit Risk; credit Default Swaps; distress risk premia; Bayesian estimation;

JEL Classification: F34; G12; G15.

*The authors are indebted to Piergiorgio Alessandri, Marianna Caccavaio, Nicola Cetorelli, Giuseppe Grande, Taneli Makinen, George Pennacchi, Marcello Pericoli, Massimiliano Rimarchi, and Marco Taboga for their constructive comments. We are also grateful for the comments received from seminar participants at the Bank of Italy, the Bank of England, and ESSEC Business School. All errors are our responsibility. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Italy.

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1 Introduction

A key feature of the 2008-2009 global crisis and of the recent debt crisis in Europe was the tight nexus between banks and sovereigns (e.g. Gennaioli, Martin and Rossi, 2013; Acharya, Dreschsler and Schnabl, 2013; Acharya and Rajan, 2013; and, Korte and Steffen, 2014). In a number of countries, the crisis originated in the banking sector, transmitted to the sovereign, and eventually fed back into the balance sheets of the banks (e.g. an *Irish-style* crisis). In contrast, in some other countries, sovereign public finances were the initial source of fragility, which then transmitted to the banks (e.g. a *Greek-style* crisis). However, regardless of where the crisis was originated, European banks' exposure to the credit risk of the domestic sovereign has been apparent since late 2008.

Banks are also exposed to the credit risk of non-domestic sovereigns. The sustainability of public debt in peripheral European countries hinders the health not only of the domestic banking sector, but also of other Eurozone countries' banking sectors through, for example, bank holdings of other countries' sovereign debt (Bolton and Jeanne, 2011). Banks' cross-border holdings of sovereign securities strengthen not only the links among banks and non-domestic sovereigns, but also among European sovereigns (Korte and Steffen, 2014). As a result, the risk of a break-up of the Eurozone, possibly due to joint defaults of large sovereigns, becomes tangible. This risk can, in turn, affect banks' balance sheets.

Taken together, these factors suggest that European banks are vulnerable not only to the risk of the domestic sovereign default, but also to the systemic risk of the Euro area sovereigns. Therefore, main goals of this paper are to first disentangle systemic and country sovereign credit risk for large European sovereigns, and then quantify and explain the cross section of individual exposures of large European banks to each type of sovereign risk. We do so by modeling the term structure of sovereign and bank credit default swaps (CDS), so that we only use publicly available information. Specifically, we first develop a multivariate reduced-form credit risk model that captures joint defaults of systemically important European sovereigns. We refer to this event as systemic sovereign risk, similar to Ang and Longstaff (2013), or simply as Euro tail risk. Notably, sovereigns can differ in their exposures to this systemic risk, as each sovereign has a different probability of defaulting when a systemic shock occurs. However, sovereigns can also default in isolation in the event of a sovereign-specific credit shock, which we label as country (sovereign) risk.

Sovereign credit risk transmits into bank credit risk through a number of channels (see, e.g., Committee on the Global Financial System [CGFS], 2011). In this way, banks are exposed to sovereign risk, and are likely to default in conjunction with a sovereign default. However, we differentiate between domestic sovereign credit risk and the systemic sovereign credit risk of the Eurozone. We also allow banks to default in the event of a bank-specific credit shock, so that bank credit risk is partly idiosyncratic (e.g. Dittmar and Yuan, 2008). As a result, banks can default in conjunction with systemic sovereign shocks, country-specific sovereign shocks, or bank-specific shocks. We then regress the cross section of the estimated bank exposures to sovereign risk, as extracted from CDS data by means of the multivariate credit model, on a number of relevant variables, such as bank size, holdings of domestic and non-domestic sovereign debt (and the associated subsidy), and expected government support.

We estimate the model in two stages. In the *first stage*, we estimate a multivariate reduced-form credit risk model, similar to that found in Ang and Longstaff (2013), on the term structures of sovereign CDS premia for Germany, France, Italy, and Spain over the 2008-2013 period. Therefore, we focus on a small but pivotal group of systemically important countries for the Eurozone. This allows us to identify a particularly severe joint credit shock that is likely not only to generate a dramatic drop in the Eurozone's real activity, but also to eventually trigger the break-up of the Eurozone itself. Of particular interest is also the fact that these countries were involved in the 2008-2009 financial crisis and in the Euro debt crisis to different extents and at different times (e.g. Ang and Longstaff, 2013; Gonzales-Hermosillo and Johnson, 2014). In addition, a large number of the most systemically important European banks are located in these countries.

In the *second stage*, we estimate each bank's exposure to the systemic and country sovereign credit risk calculated in the first-stage estimation, and bank-specific credit risk. For each country, we select only the largest banks. This leaves us with a rather homogeneous group of 21 European banks that are roughly equally split across countries.

A number of interesting results emerge from our empirical analysis. *First*, we find that there are four distinct phases characterizing the evolution of systemic sovereign risk. The main turning points are clearly associated with a few major political and economic events. The first phase spans the 2008-2009 financial crisis. After an initially subdued response to the onset of the financial crisis, systemic sovereign risk begins to increase around October 2008, which is about the time Lehman defaults, and the governments take on bank credit risk by introducing system-wide packages to rescue the banks (Panetta et al., 2009). The second phase coincides with the shift of focus from the US to the Eurozone's public finances, and the consequent surge in systemic sovereign risk. Systemic sovereign risk then wears off around the time of the introduction of the European Stability Mechanisms. Soon after, the fear that Europe's debt crisis is spiraling out of control emerges, which marks the start of the third phase. In fact, sovereign risk reaches its sample maximum in November 2011. The many measures undertaken by the European authorities might help attenuate the unprecedented rise in systemic sovereign risk. However, only with Mario Draghi's "Courageous Leap" speech in May 2012, the "Whatever It Takes" speech in July 2012, and the introduction of the Outright Monetary Transactions (OMT) in August 2012 does systemic sovereign risk finally vanish. In the fourth OMT phase, our estimates reveal that the market is no longer pricing in Euro systemic sovereign risk.

Second, Spain and Italy are the countries most exposed to systemic risk, with exposures of 6.01 and 5.96, respectively. This implies that their probabilities of defaulting as a systemic shock arrives are roughly six times higher than the probability that Germany will default. France's systemic exposure is 2.56, which is substantially lower than the corresponding figures for Spain and Italy, but higher than Germany. These estimates highlight the fragility of Spain and Italy during the Eurozone's debt crisis. However, sovereign systemic exposures tend to increase with the (average) credit risk of the sovereign. For this reason, we also look at the *systemic intensity weight*, which denotes the fraction of sovereign risk that is systemic and is readily comparable across sovereigns with different levels of risk. Interestingly, this alternative metric changes the ordering of systemic countries remarkably. In fact, the systemic component explains, on average, 66.2% and 69.7% of the credit risk of Germany and France, respectively, but only 48.5% and 44.4% of the credit risk of Italy and Spain, respectively. Thus, country sovereign risk is particularly important for Spain and Italy, while a small but significant share of German credit risk is country specific.

Third, we find strong evidence that European banks are exposed to both systemic and country sovereign credit risk. Spanish banks display the highest exposures to systemic sovereign risk, which average 4.60. They are followed by French, Italian, and German banks, with exposures of 2.84, 1.95, and 1.63, respectively. Therefore, Spanish and Italian banks are less exposed to systemic risk than their respective sovereigns. This highlights the sovereign nature of the crisis, and the pivotal role of the Spanish and Italian sovereigns. In contrast, the significant exposures of French and German banks to Euro tail risk might reflect their large holdings of cross-border assets, also including peripheral Eurozone debt. Systemic sovereign risk explains the largest fraction of French banks' credit risk (30%), which can reach a sample maximum of 81%. In contrast, systemic risk explains only 11% of Italian banks' credit risk (maximum of 39%), and it accounts for roughly 16% and 21%, respectively, of German and Spanish banks' credit risk. However, country sovereign risk is also an important determinant of banks' credit risk. In fact, it explains a substantial fraction of Spanish, Italian, and French banks' credit risk (23.6%, 18.4% and 17.0%, respectively), whereas it only explains 7% of German banks' credit risk. These results, taken together, show that sovereign credit risk, on average, accounts for roughly 45% of French and Spanish bank credit risk, while the corresponding figures for Italian and German banks are 30% and 23%.

Fourth, our estimates reveal that the market assesses that banks differ in terms of their exposures to systemic and country sovereign risk. A natural question therefore is to what extent these *estimated* bank exposures relate to commonly used measures of the bank-sovereign nexus that are based on ratings and balance sheet variables. We answer this question through a series of cross-sectional regressions, which show that: (i) the share of bank credit risk that is attributable to sovereign risk increases with bank size, while smaller banks display higher credit risk that is largely bank specific; (ii) the fraction of a bank's *systemic* sovereign credit risk increases with the bank's holdings of *non-domestic* sovereign debt and with the associated *non-domestic* subsidy, as measured in Korte and Steffen (2014), resulting from the "zero risk weight" regime that is *de facto* applied to bank holdings of Eurozone government debt; (iii) the fraction of a bank's *country* sovereign risk increases with the bank's holdings of *domestic* sovereign debt and with the associated *domestic* subsidy that results from the "zero risk weight" regime; and (iv) the higher the expected government support, the higher the probability that the bank will default when a country sovereign shock arrives.

Finally, monetary authorities appear to be increasingly interested in quantifying expected excess returns (or credit risk premia) to investors for bearing the credit risk on defaultable bonds (Stein, 2014). A clear advantage of our model is that we can easily estimate the credit *distress risk premia* implied in the CDS spreads for different horizons, and we can also identify the distress risk premia associated with each component of credit risk. As for sovereigns, we find that the percentage contribution of the total risk premium to the spreads (CRP) is particularly high and decreases with the credit risk of the sovereign. Moreover, it displays an upward-sloping term structure.

However, the behaviors of the systemic (SCRP) and country (CCRP) sovereign risk premia differ remarkably. In fact, while the term structure of the SCRPs is hump-shaped, the CCRPs term structure slopes upward. This evidence partly explains why we also find that the fraction of the CDS spreads due to systemic sovereign risk decreases with maturity. For example, the contribution of systemic risk to the one-, three-, five-, and ten-year CDS spreads for the Italian sovereign is, on average, 44%, 37%, 28% and 18%, respectively. This suggests that short- to medium-term contracts are particularly informative with regard to Eurozone's tail risk. This finding, therefore, lends support to the choice of the ECB to tackle Eurozone's systemic risk by focusing the Outright Monetary Transactions on government-issued bonds with short maturities. Moreover, banks' CRPs are lower than sovereigns' CRPs, but their term structure is generally steeper, due to the presence of bank-specific risk premia (BCRP), which also display a particularly steep upward-sloping term structure.

Related Literature. Bank exposures to sovereign risk and the implementation of adequate measures to break the tight link are at the center of the ongoing policy debate (e.g. Van Rompuy et al., 2012; Draghi, 2012; Mersch, 2013; and, Angelini, Grande and Panetta, 2014). Such delicate issue has also inspired a number of largely theoretical studies. For example, Gennaioli, Martin, and Rossi (2013) study the link between domestic government defaults and financial fragility, featuring a Greek-style crisis in which the distressed state of the public finances hinders the stability of the private banking sector. In our model, this link is captured by banks' exposures to country sovereign credit risk. Bolton and Jeanne (2011) focus on the link between a sovereign debt crisis in one country and its spread to other countries, through an integrated banking system. This channel, which is a distinctive feature of the European debt crisis, can also result in intensified links among sovereigns (Korte and Steffen, 2014). In our model, this clustering of sovereign defaults is captured by the systemic sovereign shock, and banks are also exposed to this type of sovereign risk. Our main contribution to this literature therefore lies in our provision of a quantitative framework for assessing banks' exposures to sovereign risk.

The channels through which such intimate sovereign-bank links can manifest are presented in a number of studies (e.g. CGFS, 2011; Correa et al., 2014; Angelini, Grande, and Panetta, 2014). Acharya, Dreschsler, and Schnabl (2013) were the first to model both theoretically and empirically the two-way sovereign-bank feedback. Our results fit well with their timeline. In particular, we show that, after an initial subdued response to the start of the crisis, sovereign credit risk increases in the aftermath of the introduction of the system-wide packages to rescue troubled banks. In fact, our estimates show that, around this time, the share of bank credit risk due to sovereign risk increases and that European banks are exposed thereafter to the increasing sovereign risk.

Our multivariate credit-risk model brings together the two-factor *sovereign* multivariate credit risk model of Ang and Longstaff (2013) and the two-factor *bank* multivariate credit risk model of Li and Zinna (2014). As a result, our three-factor model specification, coupled with the two-stage estimation methodology, allows us to investigate bank exposures to both systemic and country sovereign credit risk. Our study also contributes to the extensive literature on reduced-form credit risk models (Duffie and Singleton, 1999; Driessen, 2005) and on the pricing of CDS premia (Pan and Singleton, 2008; Longstaff et al., 2011; Zinna, 2013). In this regard, the novelty of our model is that the pricing of bank CDS premia is driven by three-separate stochastic processes. For this reason, our model also relates to the three-factor portfolio credit models of Longstaff and Rajan (2008) and Bahansali, Gingrich, and Longstaff (2008).

The analysis is also linked to recent attempts to measure systemic risk using only publicly available information (Adrian and Brunnermeier, 2011; Acharya, et al., 2010; Brownlees and Engle, 2012; Giglio, Kelly, Pruitt, and Qiao, 2013; Billio et al., 2012; see Bisias et al., 2012 for a survey). However, our primary focus is not on systemic risk as such but, more specifically, on the sovereign risk of European banks. Sovereign risk is not the only source of systemic vulnerability for banks. Other standard sources of risk that may have a systemic nature and pertain to banks but not to sovereigns relate for example to regulation, funding, liquidity and monetary policy (see e.g. Kashyap and Stein, 2000, 2004; Brunnermeier, 2009; Cetorelli and Goldberg, 2012). In fact, we find that bank-specific intensities of default, i.e. bank credit risk cleaned from banks' exposures to sovereign risk, still comove substantially; this confirms that (i) those alternative sources of systemic risk are empirically relevant, and (ii) our model is successful in separating them from the component that is directly associated to sovereign risk. Finally, our study is also related to the increasing number of studies focusing on the Eurozone's debt crisis and the role of European banks in particular (see, e.g., Noeth and Sengupta, 2012; Black et al., 2013; Lamont et al., 2013; Acharya and Steffen, 2014; Korte and

Steffen, 2014; Gonazale-Hermosillo and Johnson, 2014).

The remainder of the paper is organized as follows. Section 2 builds up our model. Section 3 presents the data. Section 4 discusses the econometric method and model estimation. Section 5 presents sovereign and bank credit risk, as well as a detailed cross-sectional analysis of bank exposures to sovereign risk. Section 6 focuses on the distress risk premia, and Section 7 concludes the paper. A separate Internet Appendix provides a detailed description of the estimation methodology and contains additional materials on the empirical results.

2 The Model

Credit Default Swap Pricing. A credit default swap (CDS) is an insurance contract, in which the protection seller takes on the risk of an agreed credit event against the payment of a premium from the protection buyer. The protection seller covers the loss that the protection buyer might incur contingent on the credit event (protection leg). In return, the protection buyer pays an annuity to the protection seller (premium leg). The protection buyer stops paying the premium to the seller when the contract reaches maturity or before that point if the credit event takes place. As a result, the fair swap premium is determined such that the default swap contract has zero value at inception.

Fix a probability space $(\Omega, \mathbb{F}, \mathbb{Q})$ such that the complete filtration $\{\mathbb{F}_t\}_{t\geq 0}$ satisfies the usual conditions, where $\mathbb{Q}$ denotes the risk-neutral martingale measure (Harrison and Kreps (1979)). Let $CDS(t, M)$ denote the annualized premium paid by the protection buyer, which is determined at time t for a contract maturing in M years, r_t the instantaneous default-free interest rate, and λ_t the intensity of a credit event. If we assume that the premium is paid continuously, the present value of the premium leg of a credit default swap is given by:

$$P(CDS, t, M) = CDS(t, M)E^{\mathbb{Q}}\Big[\int_t^{t+M} \exp\Big(-\int_t^s r_u + \lambda_u du\Big)ds\Big], \tag{1}$$

and the present value of the protection leg, given a constant risk-neutral fractional recovery $R^{\mathbb{Q}}$, is instead given by:

$$PR(R^{\mathbb{Q}}, t, M) = (1 - R^{\mathbb{Q}})E^{\mathbb{Q}}\Big[\int_t^{t+M} \lambda_s \exp\Big(-\int_t^s r_u + \lambda_u du\Big)ds\Big]. \tag{2}$$

The fair value of $CDS(t, M)$ is then derived by equating the protection leg $PR(R^{\mathbb{Q}}, t, M)$ and the premium leg $P(CDS, t, M)$:

$$CDS(t, M) = \frac{(1 - R^{\mathbb{Q}})E^{\mathbb{Q}}\Big[\int_t^{t+M} \lambda_s \exp\Big(-\int_t^s r_u + \lambda_u du\Big)ds\Big]}{E^{\mathbb{Q}}\Big[\int_t^{t+M} \exp\Big(-\int_t^s r_u + \lambda_u du\Big)ds\Big]}. \tag{3}$$

This simple reduced-form framework, in which the credit event is modeled as an unpredictable jump of a Poisson process driven by the intensity λ_t (see Duffie and Singleton, 1999; among others), is suitable for the pricing of both sovereign and bank default swaps. More fundamentally, the specification of the intensity λ_t, coupled with the estimation methodology, is central to the identification of the different sources of credit risk allowing for default clustering across entities. In what follows, we describe our model of sovereign and bank credit risk.

Sovereign Credit Risk. We build on Ang and Longstaff (2013), such that we assume that two types of credit events can trigger sovereign defaults. First, sovereigns can default in the event of country (i.e. sovereign-specific) shocks. Second, sovereigns can experience joint defaults (*i.e.*, default clustering), so that there is a systemic intensity that jointly determines their credit risk. Thus, during a systemic event every sovereign can eventually default, but sovereigns' exposures to this systemic event can differ. Specifically, sovereign i's default intensity is composed of the country intensity ($C_{t,i}$) and the scaled systemic intensity ($\alpha_i S_t$):

$$\lambda_{t,i} = \alpha_i S_t + C_{t,i}, \tag{4}$$

where the sovereign exposure α_i determines the sovereign-specific probability of default when a systemic shock arrives and can therefore only take non-negative values. In sum, we focus on two types of sovereign risk, which we refer to as 'systemic' and 'country specific'.

In line with Longstaff et al. (2005), among others, we assume that the country-specific intensity $C_{t,i}$ follows a standard square-root (CIR) process under the risk-neutral measure:

$$dC_{t,i} = (\eta_i - \kappa_i^{\mathbb{Q}} C_{t,i})dt + \sigma_i \sqrt{C_{t,i}} dW_{t,i}^{\mathbb{Q}}, \tag{5}$$

where η_i, $\kappa_i^{\mathbb{Q}}$, and σ_i are constants and the Brownian motion $W_{t,i}^{\mathbb{Q}}$ is sovereign specific.[1] Similarly, the common intensity S_t follows the CIR process:

$$dS_t = (\eta - \kappa^{\mathbb{Q}} S_t)dt + \sigma \sqrt{S_t} dB_t^{\mathbb{Q}}, \tag{6}$$

where η, $\kappa^{\mathbb{Q}}$, and σ are the constants, and the Brownian motion is now $B_t^{\mathbb{Q}}$, which is independent of $W_{t,i}^{\mathbb{Q}}$.

Bank Credit Risk. We model bank credit risk such that banks can default not only in conjunction with idiosyncratic (or bank-specific) shocks, but also in conjunction with sovereign credit shocks. In particular, banks are exposed to systemic sovereign credit risk and to the

[1]The squared-root process is particularly suitable for modelling the intensity of default for a number of reasons: (i) standard results, such as Duffie et al. (2000), hold so that closed-form solutions for the building-blocks of the CDS pricing can be derived; (ii) under mild conditions, the squared-root process only takes positive values; and (iii) the volatility is state dependent. For these reasons, it has been widely used in the credit risk literature (see, for example, Driessen, 2005; Ang and Longstaff, 2013; Li and Zinna, 2013).

credit risk of the domestic sovereign. As a result, the intensity of default of bank j located in country i is the sum of the scaled systemic intensity ($\alpha_{i,j} S_{t,i}$), the scaled country intensity ($\gamma_{i,j} C_{t,i}$), and the idiosyncratic intensity ($I_{t,i,j}$):

$$\lambda_{t,i,j} = \alpha_{i,j} S_t + \gamma_{i,j} C_{t,i} + I_{t,i,j}, \tag{7}$$

where $\alpha_{i,j}$ and $\gamma_{i,j}$ are non-negative constants determining the bank's probability of defaulting as systemic and country sovereign credit events occur, respectively. Similar to S_t and $C_{t,i}$, we assume that also the bank-specific intensity ($I_{t,i,j}$) follows a squared-root dynamics:

$$dI_{t,i,j} = (\eta_{i,j} - \kappa_{i,j}^{\mathbb{Q}} I_{t,i,j})dt + \sigma_{i,j}\sqrt{I_{t,i,j}}dZ_{t,i,j}^{\mathbb{Q}}, \tag{8}$$

where $\eta_{i,j}$, $\kappa_{i,j}^{\mathbb{Q}}$, and $\sigma_{i,j}$ are the constants and the Brownian motion is now $Z_{t,i,j}^{\mathbb{Q}}$, which is independent of $B_t^{\mathbb{Q}}$ and $W_{t,i}^{\mathbb{Q}}$.[2]

Given the specifications of default risk, (4) and (7), and the square-root dynamics of the individual intensities, (5), (6), and (8), the expectations in (1) and (2) can be solved analytically by using the transform approach of Duffie, Pan, and Singleton (2000). We can thus easily find the fair value $CDS(t, M)$ of both sovereign and bank CDS spreads (see Appendix A).

Finally, to close the model, we employ the *essentially* affine default price of risk for the diffusion risks in (5), (6), and (8), as in Duffee (2002). As a result, the intensities conveniently follow the square-root processes also under the objective measure ($\mathbb{P}$):

$$\begin{aligned} dS_t &= (\eta - \kappa^{\mathbb{P}} S_t)dt + \sigma\sqrt{S_t}dB_t^{\mathbb{P}}, & (9)\\ dC_{t,i} &= (\eta_i - \kappa_i^{\mathbb{P}} C_{t,i})dt + \sigma_i\sqrt{C_{t,i}}dW_{t,i}^{\mathbb{P}}, & (10)\\ dI_{t,i,j} &= (\eta_{i,j} - \kappa_{i,j}^{\mathbb{P}} I_{t,i,j})dt + \sigma_{i,j}\sqrt{I_{t,i,j}}dZ_{t,i,j}^{\mathbb{P}}, & (11)\end{aligned}$$

where $B_t^{\mathbb{P}}$, $W_{t,i}^{\mathbb{P}}$ and $Z_{t,i,j}^{\mathbb{P}}$ are Brownian motions defined under the objective measure, which are still mutually independent. Therefore, instantaneous systemic, country-specific and bank-specific distress risk premia depend on $\pi = \kappa^{\mathbb{Q}} - \kappa^{\mathbb{P}}$, $\pi_i = \kappa_i^{\mathbb{Q}} - \kappa_i^{\mathbb{P}}$ and $\pi_{i,j} = \kappa_{i,j}^{\mathbb{Q}} - \kappa_{i,j}^{\mathbb{P}}$, respectively.[3]

[2]This assumption of independent Brownian motions is mainly adopted to preserve model tractability; correlated shocks complicate the pricing of the CDS, the estimation and the distress risk premium decomposition. For this reason, this assumption is widely used in credit risk multivariate models (Ang and Longstaff, 2013; and Li and Zinna, 2013). However, this comes at the cost of not being able to study the transmission of shocks, or contagion, among systemic, country-specific and bank risk. If instead, for instance, the $\mathrm{dW}_{t,i}$ were correlated among themselves and with dB_t it would then be possible (subject to additional identifying assumptions) to (i) investigate sovereign contagion among countries, and (ii) assess each country's role in causing variations in sovereign systemic risk (S_t).

[3]The extended market price of risk proposed by Cheridito, Filipovic and Kimmel (2007) is a more general specification. Under this specification the mean reversion parameters and the unconditional mean parameters, are allowed to change under $\mathbb{P}$ and $\mathbb{Q}$. However, this parametric form of the market price of risk requires the Feller condition to be satisfied both under $\mathbb{P}$ and $\mathbb{Q}$ in order to avoid arbitrage opportunities. In practice, this

3 The Data

3.1 Sample Selection

In order to identify a particularly severe joint credit event that can have significant consequences for the Eurozone, we focus on the four largest European countries: Germany, France, Italy and Spain. The severity of such an event is likely to not only generate a dramatic drop in real activity, with the Eurozone economy sinking into a recession, but also to eventually trigger the tail risk of a breakup of the Euro area. Therefore, differently from Ang and Longstaff (2013), we focus on a smaller, but pivotal, group of systemically important countries for the Euro area. Nevertheless, we adopt Ang and Longstaff's (2013) terminology in that we define (Eurozone sovereign) systemic risk as the probability that more than one country will default at the same time.[4] Moreover, the evolution of credit risk in these countries is characterized by remarkable differences, as they were involved in the 2008-2009 financial crisis and later in the Eurozone debt crisis to different extents and at different times (Ang and Longstaff, 2013; Gonzales-Hermosillo and Johnson, 2014). Furthermore, by choosing this set of countries, we can select a sufficiently large number of systemically important banks for each country. In the subsequent analysis, this enables us to compare the differing banking sectors, especially with regard to their exposures to systemic and country sovereign credit shocks.

Ample anecdotal evidence suggests that each banking system displayed a certain role in the transmission of the crisis in the Eurozone. In the buildup to the 2008-2009 crisis, Europe leveraged its international balance sheet significantly by issuing considerable sovereign debt and bank debt, and using the proceeds to buy substantial amounts of highly rated US mortgage-backed securities and other fixed-income products (Bernanke, Bertaut and Kamin, 2011). In particular, German and French banks suffered substantial losses as a consequence of the crisis in the US mortgage market (Acharya and Schnabl, 2010). In this way, European banks contributed to the unfolding of the Euro debt crisis. German and French banks were also highly exposed to the debt of Greece, Portugal, Ireland, Italy and Spain, until the start of the Euro crisis (Lindner, 2013). In contrast, the impact of the initial phase of the crisis on Spanish banks was limited, reflecting their traditional retail banking models. However, in 2009, the downturn in the real economy directly affected Spanish banks' balance sheets, through asset impairments, especially impairments of assets linked to the real-estate development sector

implies that a series of non-linear constraints must be implemented in the estimation. The imposition of these restrictions in our multivariate credit model comes at a high computational cost, and deteriorates the pricing of the term structure of CDS. For these reasons, we use the more parsimonious essentially affine market price of risk, similar to Feldhutter and Nielsen (2012) and Li and Zinna (2014), among others.

[4]There is a widespread debate on what is a truly systemic event (see, for example, Hansen, 2013). Events that can lead to the breakdown of or major dysfunctions in financial markets with severe implications for real activity are generally denoted as systemic events. In this study, we refer to the joint defaults of sovereigns as Eurozone systemic sovereign risk, or simply as systemic risk in line with Ang and Longstaff (2013). However, such events could also be defined as Eurozone tail risk or systematic risk. For our analysis, the crucial point though is to disentangle this event from country-specific sovereign risk.

(Bank of Spain, 2011). This source of fragility, in turn, exposed Spanish banks to the tensions that still prevailed in international markets. Notably, the fragility of the Italian banks was enhanced by their direct exposure to domestic sovereign risk.

These considerations lead to our explanation of how we select the banks for each country. Above all, we are interested in systemically important banks. For France and Italy, the choice is rather straightforward, as we select the same banks that are included in the European Banking Authority (EBA) stress-testing exercise, which results in four French banks and five Italian banks.[5] In contrast, the German and Spanish banking systems are much more fragmented, as documented by the large number of banks included in the EBA stress test. However, as we aim to focus our analysis on a homogeneous group of large European banks, we only select German and Spanish banks with total asset of more than 100 USD, for which a sufficiently liquid term structure of CDS premia is available. Furthermore, we try not include subsidiaries, with only few exceptions. This selection criterion leaves us with seven German banks and five Spanish banks. As a result, we end up with a total of 21 banks, which are roughly equally split across countries. The names of the individual banks are provided in Table 1.

3.2 The Term Structure of CDS Prices

The data for this study include the term structures of sovereign and bank CDS spreads for the one-, three-, five-, seven- and ten-year maturities. The notional of the sovereign CDS contracts is specified in dollars, whereas the notional of bank CDS contracts is specified in euros, thus reflecting the most liquid contracts.[6] The data are obtained from Credit Market Analytics (CMA), and cover weekly (Wednesday) ask, mid and bid quotes of CDS contracts over the period from January 2008 to December 2013.[7] Our sample is therefore of particular interest as it covers the 2008-2009 global crisis and the bulk of the Euro debt crisis.

Table 1 presents summary statistics of the five-year CDS mid quotes. The average sovereign CDS spreads range from 43 basis points for Germany to 221 basis points for Spain, whereas they are 80 and 213 basis points for France and Italy, respectively. The average spreads for German banks range from 112 basis points for DZ Bank to 206 basis points for HSH Nordbank. For French banks, they range from 122 basis points for BNP Paribas to 185 basis points for

[5]Note that, instead of using Groupe BPCE, we use its investment bank, Natixis, for which the term structure of CDS premia is available. Also note that the same set of banks is included in the latest Financial System Stability Assessments (FSAP). The FSAP is a comprehensive in-depth assessments of a country's financial sector carried out by the International Monetary Fund and the World Bank. The only exception is Groupe Credit Mutuel, which is included in the French FSAP but not in the EBA stress test.

[6]Eurozone sovereign CDS contracts are also available in euros. However, these contracts leave the protection buyer exposed to currency risk, i.e. depreciation of the euro, in the event of sovereign default. For this reason, euro-denominated CDS contracts for European sovereigns are substantially less liquid than dollar-denominated contracts. In contrast, European banks' CDS contracts are generally denominated in euros.

[7]CMA database quotes lead the price-discovery process in comparison with the quotes provided by other databases (Mayordomo, Peña and Schwartz, 2010).

Natixis. For Italian banks, they range from 199 basis points for Intesa Sanpaolo to 329 basis points for Banco Popolare, and for Spanish banks, from 201 basis points for Banco Santander to 401 basis points for Banco Popular Espanol. Therefore, there is substantial cross-sectional variability in the average credit risk of the banks within each country. More fundamentally, the sovereign credit risk of Germany and, to a lesser extent, of France is sensibly lower than the credit risk of any of their domestic banks included in our sample. In contrast, the sovereign credit risk of Italy and Spain seems to be more closely related to the credit risk of the domestic banks. In fact, some of the largest Italian and Spanish banks, such as Intesa Sanpaolo, Banco Santander and BBVA, trade on average at lower CDS spreads than the domestic sovereign.

Moreover, the median CDS premia of both sovereign and bank CDS premia are slightly lower than the mean premia, with the only exception of Spain and a few of Spanish banks. Italian and Spanish sovereign spreads also display more variation, ranging from a minimum of 25 and 24 basis points to a maximum of 577 and 617 basis points, respectively. A similar pattern holds for their banks. In fact, the spreads for Banco Popolare range from a minimum of 69 basis points to a maximum of 951 basis points, and the spreads for Banco Popular Espanol range from a minimum of 92 basis points to a maximum of 926 basis points. In terms of the autocorrelation statistics, sovereign CDS premia are highly autocorrelated (roughly 0.98). Moreover, sovereign CDS premia tend to be more autocorrelated than the bank CDS premia (see, e.g., Germany and France), which are also highly autocorrelated.

We present the average term structures of the CDS mid quotes in the Internet Appendix. The average term structures are generally upward sloping. However, the shape of the term structure is convex, with the distance between the five- and one-year spreads being substantially greater than the distance between the ten- and five-year spreads. This stylized fact contrasts with the inspection of the bid-ask average term structures, which are generally either downward sloping or hump shaped. This evidence confirms the limited liquidity of the one-year contract (Pan and Singleton, 2008). However, despite its limited liquidity, the inclusion of the one-year contract is important, as this contract promptly reacts to episodes of strongly enhanced risk, which can result in the inversion of the term structure. Finally, sovereign CDS contracts are generally more liquid than bank CDS contracts, with one-year bid-ask spreads being of comparable magnitude to those of the other maturities for Germany and Spain.

4 Model Estimation and Inference

The main objective of this study is to determine banks' exposures to the different sources of sovereign credit risk. We do so by implementing a two-stage estimation procedure. In the first stage, we estimate a multivariate reduced-form credit model on the sovereign CDS premia, using the two-factor specification described in Section 2. Similar to Ang and Longstaff

(2013), this enables us to identify two sources of sovereign credit risk: systemic and country specific. In the second stage, we estimate each bank's exposure to Eurozone systemic and country sovereign risk, the idiosyncratic intensity, and the parameters driving its dynamic under $\mathbb{P}$ and $\mathbb{Q}$. We propose a Bayesian estimation method, which is particularly suitable for continuous time models (Johannes and Polson, 2009), and builds on the algorithm developed by Li and Zinna (2013).

4.1 State-Space Representations

A natural way to proceed is to cast our model into a state-space framework. We first focus on the state space of the sovereign multivariate model (stage one), we then move to the state space of the individual banks (stage two). The discretized transition equations, based on the standard Euler scheme applied to a small time interval τ, take the form of:

$$\begin{aligned} S_t &= \eta\tau + (1-\kappa^{\mathbb{P}}\tau)S_{t-\tau} + \sigma\sqrt{\tau S_{t-\tau}}b_t, && (12)\\ C_{t,i} &= \eta_i\tau + (1-\kappa_i^{\mathbb{P}}\tau)C_{t-\tau,i} + \sigma_i\sqrt{\tau C_{t-\tau,i}}w_{t,i}, && (13) \end{aligned}$$

where b_t and $w_{t,i}$ are mutually independent standard normal noises. Thus, there are five transition equations, of which one is systemic and four are country specific. Then, for a generic sovereign i, we collect mid-quote CDS prices for the 1-, 3-, 5-, 7- and 10-year maturities at each time t, and stack them in the vector $\mathrm{CDS}_{t,i}^{obs}$. Thus, the observation space for sovereign i at time t is given by:

$$\mathrm{CDS}_{t,i}^{obs} = f\left(S_t, C_{t,i}, \theta^{\mathbb{Q}}, \theta_i^{\mathbb{Q}}, \alpha_i\right) + \epsilon_{t,i}, \qquad \epsilon_{t,i} \sim N\left(0, \Sigma_{t,i}\right), \tag{14}$$

where $f(\cdot)$ is the two-factor CDS pricing function, which depends on the systemic and country sovereign intensities, the risk-neutral parameters $\theta^{\mathbb{Q}} = [\eta, \kappa^{\mathbb{Q}}, \sigma]$ and $\theta_i^{\mathbb{Q}} = [\eta_i, \kappa_i^{\mathbb{Q}}, \sigma_i]$, and the sovereign exposure (α_i).[8] The CDS contract of maturity M of sovereign i is assumed to be priced with normally distributed errors with a mean of zero and a standard deviation of $\sigma_{\epsilon,i}\left|Bid_{t,i}(M) - Ask_{t,i}(M)\right|$. Therefore, the parameter $\sigma_{\epsilon,i}$ is common across maturities and measures the degree of model mispricing relative to the observed bid-ask spreads. Thus, $\Sigma_{t,i}$ is a diagonal matrix with pricing-error variances on the diagonal entries that vary over time and across maturities with the bid-ask spreads. This is an important feature of the model, as there is strong evidence that liquidity varies across maturities, such that it is particularly scarce at the 1-year maturity and somewhat less scarce at the 10-year maturity. Moreover, making the variance dependent on the bid-ask spreads allows us to account for the possibility that the fit of our model deteriorates during times of market turmoil when liquidity drops and bid-ask

[8]The pricing of the CDS premia based on the multivariate model described in equations (4)-(6) closely follows Ang and Longstaff (2013) and Li and Zinna (2013). To economize on space, we refer the reader to those studies.

spreads consequently widen. A similar specification for the pricing error variance is also used by Pan and Singleton (2008). In sum, the measurement space stacks together the measurement equations of the four sovereigns $\text{CDS}_t^{obs} = \left[\text{CDS}_{t,GER}^{obs}, \text{CDS}_{t,FRA}^{obs}, \text{CDS}_{t,ITA}^{obs}, \text{CDS}_{t,ESP}^{obs}\right]$, so that 20 sovereign CDS prices are collected at each time t.

We now move on to describing the state-space representation of the second-stage estimation. The second-stage estimation is carried out bank by bank. As a result, the dimensionality of the measurement space decreases substantially, as it only includes the term structure of the CDS mid quotes of the focal bank. However, there is an additional transition equation that describes the evolution of the bank's idiosyncratic intensity. As a result, the pricing is now based on the three-factor pricing function $s(\cdot)$, as described in Appendix A. Specifically, the measurement space for bank (i, j) is given by:

$$CDS_{t,i,j}^{obs} = s\left(S_t, C_{t,i}, I_{t,i,j}, \theta^{\mathbb{Q}}, \theta_i^{\mathbb{Q}}, \theta_{i,j}^{\mathbb{Q}}, \alpha_{i,j}, \gamma_{i,j}\right) + \epsilon_{t,i,j}, \qquad \epsilon_{t,i,j} \sim N\left(0, \Sigma_{t,i,j}\right), \tag{15}$$

where $\theta_{i,j}^{\mathbb{Q}} = [\eta_{i,j}, \kappa_{i,j}^{\mathbb{Q}}, \sigma_{i,j}]$ are the risk-neutral parameters driving the dynamics of $(I_{t,i,j})$, and $\Sigma_{t,i,j}$ is the measurement error variance-covariance matrix, which has a diagonal form and varies over time. The standard deviation associated with the observed CDS quote of maturity M is $\sigma_{\epsilon,i,j}\left|Bid_{t,i,j}(M) - Ask_{t,i,j}(M)\right|$. Finally, the additional transition equation is:

$$I_{t,i,j} = \eta_{i,j}\tau + (1 - \kappa_{i,j}^{\mathbb{P}}\tau)I_{t-\tau,i,j} + \sigma_{i,j}\sqrt{\tau I_{t-\tau,i,j}}z_{t,i,j}, \tag{16}$$

where $z_{t,i,j}$ is a standard normal noise.

4.2 Identifying Restrictions

In order to avoid the identification problem, we follow Ang and Longstaff (2013), in that we normalize the German exposure to the systemic intensity to unity ($\alpha = 1$). This restriction effectively rescales the other sovereigns' systemic exposures, such that α_i provides information on the probability that sovereign i will default in the event of a systemic shock relative to the probability that Germany defaults. However, in contrast to Ang and Longstaff (2013), we allow Germany to default not only in the event of a systemic shock but also in the event of a sovereign-specific shock, in line with the other sovereigns.[9] In this way, we can also investigate the exposure of German banks to the credit risk of the domestic sovereign.

In the second stage, no further identification restriction is required. Bank exposures to systemic risk ($\alpha_{i,j}$) provide information on the bank's default probability relative to the probability that Germany will default in the event of a systemic shock. Similarly, the country

[9] To implement this richer specification while still guaranteeing that the model is identified, we find that it is useful to fix the systemic sigma (σ). We do this by fixing the systemic sigma to the value resulting from a preliminary estimation of the model based on the same identifying restrictions found in Ang and Longstaff (2013).

exposure ($\gamma_{i,j}$) provides information on the bank's probability of defaulting relative to the probability that the *domestic* sovereign i will default in the event of a country shock.

Finally, we assume a constant risk-free interest rate, similar to Pan and Singleton (2008) and others, which substantially simplifies the pricing of the CDS. We also fix the risk-neutral loss rate given default at 50%, *i.e.* $R^{\mathbb{Q}} = 0.50$ (see, e.g., Li and Zinna, 2013).

4.3 Bayesian Inference

Bayesian methods allow us to approximate the posterior distribution of parameters and states given the entire set of observations, $p(\Theta, X|D)$, where Θ denotes the parameters, X denotes the latent states, and $D = \{CDS_t^{obs}\}_{t=1}^T$ denotes the data. Direct sampling from the posterior distribution $p(\Theta, X|D)$ is often not possible due to its complicated form. However, Markov Chain Monte Carlo (MCMC) methods allow us to simulate using simpler conditional distributions. Specifically, according to the Bayes' rule, the posterior density can be decomposed such as:

$$p(\Theta, X|D) \propto p(D|X, \Theta)p(X|\Theta)p(\Theta), \tag{17}$$

where $p(D|X, \Theta)$ denotes the likelihood function conditional on the states and the parameters; $p(X|\Theta)$ is the density of states conditional on the parameters; and $p(\Theta)$ is the prior density of the parameters. We can then iteratively draw from the full conditionals $p(\Theta|X, D)$ and $p(X|\Theta, D)$. Conveniently, the parameter set Θ and the state set X can be further broken into smaller blocks.

The first-stage estimation closely follows Li and Zinna (2013). There are, however, two differences worth mentioning. First, Li and Zinna (2013) use an identification strategy similar to Ang and Longstaff (2013). Second, they assume that the pricing-error volatility is constant over time and equal across maturities. With these differences in mind, the main steps of the MCMC estimation are as follows. First, we draw the parameters conditional on the data and the states. The objective mean-reversion parameters $\kappa^{\mathbb{P}}$ and $\kappa_i^{\mathbb{P}}$ and variances of measurement errors σ_ϵ^2 and $\sigma_{\epsilon,i}^2$ have conjugate priors with normal and inverse Gamma posterior distributions, respectively. Thus, we can sample directly from their posterior distributions using the Gibbs sampler. In contrast, we use the slice-sampling method proposed by Neal (2003) to draw the rest of the parameters, as it is not feasible to sample directly from their full conditional posterior distributions. We then draw the latent states individually, conditional on the parameters and the data. As the posterior distributions are again non-standard, we again use the slice-sampling method. As a result, we use a hybrid MCMC algorithm that combines the Gibbs sampler with a series of slice-sampling steps. Samples of draws are then obtained by repeatedly simulating from the conditional distribution of each block in turn. It is standard to treat these draws (beyond a burn-in period) as variates from the target posterior distribution.[10]

In the second-stage we estimate separately for each bank (i, j) its latent intensity $I_{t,i,j}$; the associated risk-neutral parameters $\theta^{\mathbb{Q}}_{i,j} = [\eta_{i,j}, \kappa^{\mathbb{Q}}_{i,j}, \sigma_{i,j}]$; the objective mean reversion $\kappa^{\mathbb{P}}_{i,j}$; the systemic, $\alpha_{i,j}$, and country-specific, $\gamma_{i,j}$, sovereign exposures; and, the pricing-error volatility $\sigma_{\epsilon,i,j}$. We draw these parameters and states in fashion similar to that seen in the first stage. The key difference is that we draw these parameters conditional on the parameter and state estimates of the first stage.

Bayesian estimation methods are particularly suitable for continuous-time financial models (Johannes and Polson, 2009). They allow us to simultaneously estimate model parameters and latent factors, and to quantify the uncertainty around the estimates. We can, for example, easily quantify the noise that first-stage estimates induce entering the second-stage estimation.[11] Moreover, post-estimation calculations, such as the distress risk premia, are based on highly non-linear functions of the estimated parameters. Notably, it is relatively straightforward to quantify the uncertainty around these estimates in a Bayesian context, while it is relatively complicated in a frequentist context (Bauer, 2011).

4.4 Parameter Estimates

First-stage Estimates. We now present the parameter estimates and discuss the model fit. Table 2 reports the estimates of the parameters driving the systemic (Panel A) and country-specific intensities (Panel B) that result from the first-stage estimation. The mean reversion parameters under the risk-neutral measure are negative. This is not an uncommon feature in term-structure models, and it does not pose a problem, as the mean reversion parameters under the objective measure are positive, indicating that the processes are indeed stationary under the objective measure. Notably, the speeds of mean reversion under the objective (risk-neutral) measure increase (decrease) with the credit risk of the sovereign, *i.e.* the speeds of mean reversion are 1.43 (-0.69) for Germany and 0.39 (-0.30) for Spain. This evidence suggests not only that a credit risk premium is priced into the Eurozone sovereign CDS premia, but also that this premium is a particularly important driver of less risky sovereign CDS premia.

[10] The priors used in this study are diffuse, and their distributions are chosen for convenience using a number of earlier papers (e.g., Johannes and Polson, 2009). With regard to the computational details, we perform 40,000 replications, of which the first 20,000 are burned-in. We then save 1 of every 10 draws of the last 20,000 replications of the chain so that the draws are independent.

[11] In our study, the sovereign credit model is embedded within the bank credit model. For this reason, it is convenient to estimate the model in two stages. However, the second-stage estimator includes noise induced by the first-stage estimates (both states and parameters in our case). Therefore, to further investigate this issue, we estimated the second-stage parameters, taking the noise around the parameters estimated in the first stage into account. We did so by repeating the estimation of the second-stage parameters for each of the retained draws. We then used the resulting distribution of the estimates to quantify the impact of the noise around the first-stage estimates on the second-stage estimates. Overall, we found that the impact is limited. This is because the first-stage parameter estimates, which enter the second-stage estimation, are estimated rather precisely. In fact, the only parameters displaying large confidence intervals are the $\kappa^{\mathbb{P}}$ parameters, which do not enter the second-step estimation. The results are available upon request.

The systemic intensity also commands a particularly large risk premium, given that the risk-neutral and objective speeds of mean reversion are -0.48 and 1.33, respectively. Also notable is that the parameters are estimated very precisely, with the exceptions of the objective speeds of mean reversion parameters, which are notoriously hard to estimate, especially for rather short samples.

The analysis of the measurement standard deviations is indicative of the goodness-of-fit of the model. However, it is worth emphasizing that these parameters determine the degree of model mispricing relative to the observed bid-ask spreads. For this reason, we complete the investigation of the model fit by looking at the mean absolute pricing errors (MAPE) and the mean absolute percentage pricing errors (MAPPE), which are presented in the Internet Appendix. As they control for the level of the CDS premia, the MAPPEs help us compare pricing errors across maturities and sovereigns. We find that the model prices the 5-, 7- and 10-year maturities particularly well, and that it prices 3-year maturity well with the exception of Germany. Specifically, the MAPPE (MAPE) for the five-year contract ranges from a minimum of 2.9 percent (4.5 basis points) for Spain to a maximum of 9.6 percent (3.9 basis points) for Germany. The pricing of the one-year contract is relatively poor, which is consistent with a number of previous studies. This may be due to its relatively low liquidity, as also reflected by its relatively large bid-ask spreads.

Second-stage Estimates. The parameter estimates of the individual bank-idiosyncratic intensities in the second stage are generally in line with the first-stage estimates (see the Internet Appendix). That is, the parameters are precisely estimated, the intensities are stationary under the objective measure, and there is evidence of a risk premium attached to the idiosyncratic intensity. However, there are also some important differences. For a considerable number of banks, the idiosyncratic intensity is also stationary under the risk-neutral measure. Moreover, the distance between the objective and the risk-neutral mean reversion parameters of the idiosyncratic intensities is generally smaller than the distance between the objective and the risk-neutral mean reversion parameters of the systemic and country-specific sovereign intensities. Taken together, these results suggest not only that there is a risk premium associated with each component, but also that the properties of these risk premia can vary considerably. The term structure of the risk premia components is carefully analyzed in Section 6.

The pricing-error statistics, also found in the Internet Appendix, largely conforms to the considerations raised relative to the first-stage estimation. However, it is worth noting that the MAPPEs of the sovereigns are smaller than those of the domestic banks, which holds for every maturity. The only exception is Germany.

5 Sovereign and Bank Credit Risk

In this section, we first present the sovereign risk estimates, focusing on the systemic and country sovereign intensities. We then analyze individual banks' exposures to systemic and country-specific sovereign risk. We relate the cross section of individual banks' exposures to: bank size; holdings of domestic and non-domestic sovereign debt, and the associated sovereign domestic and non-domestic subsidies; and the expected government support. We complement this analysis with a discussion of the results.

5.1 Sovereign Credit Risk

Systemic Credit Risk. Figure 1 presents the time-series estimate of the systemic sovereign intensity (S_t) with the 95% confidence intervals, showing that the intensity is estimated very precisely. It is evident that four distinct phases characterize the evolution of sovereign systemic risk, and that the main turning points are largely associated with a few political events (dotted lines).[12]

The first phase shows an initial subdued reaction of systemic sovereign risk to the onset of the crisis, which was largely located in the US mortgage market. This calm period ends with Lehman's default and the introduction of the system-wide rescue packages by European governments.[13] Thereafter, systemic sovereign risk rises steadily, reaching its peak of 30 basis points around the time the US authorities announce a series of initiatives, such as the Troubled Asset Relief Program (TARP). The turning point coincides with the introduction of the Term Asset-Backed Securities Loan Facility (TALF). Then, the G20 agrees to treble the resources available to the IMF to $750 billion, which helps consolidate the drop in systemic risk. Therefore, the first period essentially spans the 2008-2009 financial crisis.

The second phase, which starts in the late 2009, brings a shift in focus from the US to the Eurozone's public finances. In particular, the sudden increase in systemic risk stops with the introduction of the first austerity package for Greece. However, this drop in systemic credit risk is short lived. The introduction of the European Financial Stability Facility (EFSF) impedes the acceleration of systemic sovereign risk. However, only when the European finance ministers replace the EFSF with a permanent bailout fund for the region of €500 billion, which is called European Stability Mechanism (ESM), does the systemic sovereign risk finally fade.

The third phase starts in the summer of 2011 with an unprecedented spike in the systemic intensity of around 50 basis points. The increase stops around the time that Spain passes a constitutional amendment regarding a "golden rule", which aims to keep future budget

[12]The introduction of new policies by domestic and international authorities can affect asset prices, and therefore the risk perceived by investors, by resolving the uncertainty. This result is therefore consistent with the emerging literature that links political uncertainty to stock prices and the price of risk (Pastor and Veronesi, 2012, 2013; David and Veronesi, 2014; and, Kelly, Pastor, and Veronesi, 2014).

[13]See Panetta et al. (2009) for an assessment of financial-sector rescue programmes.

deficits within a strict limit. Around the same time, Italy passes a €50 billion austerity plan to balance the budget by 2013. However, in the second half of 2011, fear that Europe's sovereign debt crisis is spiraling out of control begins to emerge. In fact, our systemic risk intensity reaches its sample maximum value of roughly 70 basis points in November 2011. This, in turn, supports the anecdotal evidence that the tensions became systemic around this time. In response to this heightened tension, the European Central Bank announces the introduction of the Longer-term Refinancing Operations (LTRO), and the fiscal pact first agreed in December is finally signed off in January 2012. These actions prove effective in that the market perception of systemic risk consequently drops. Furthermore, the Greek parliament passes an unpopular austerity bill in February 2012, which might also contribute to the drop in systemic sovereign risk. All in all, these measures contribute to temporarily attenuating the comovement in sovereign credit risk, which rebounds soon thereafter. However, only with Mario Draghi's "Courageous Leap" speech in May 2012, the "Whatever It Takes" speech in July, and the introduction of the Outright Monetary Transactions (OMT) in August, does systemic sovereign risk, as priced by the CDS market, finally vanish.

The fourth OMT phase, which spans the period from September 2012 to the end of the sample in December 2013, is characterized by investors no longer pricing systemic sovereign risk.

Systemic Sovereign Exposures. We now turn to the *cross-sectional* dimension of sovereign systemic risk. We do this by first presenting the systemic exposures (α_i), as reported in Table 2, which indicate sovereign i's probability of defaulting in conjunction with a systemic shock. However, recall that the systemic exposure of Germany is fixed at one, as described in Section 4.2. As a result, α_i denotes the ratio of the conditional systemic probability of default of sovereign i to that of Germany. In short, sovereigns' systemic exposures are re-scaled with respect to the systemic exposure of Germany. France, for example, has a systemic exposure of 2.56, which indicates that France has a probability of defaulting that is roughly two and a half times higher than that of Germany in the event of a systemic shock. Italy and Spain display systemic exposures of 5.96 and 6.01, respectively. Therefore, Italy and Spain have the highest probabilities to default in the event of a systemic shock. This result is consistent with anecdotal evidence suggesting that the tensions became systemic in the summer of 2011 as they spread to the Italian and Spanish government securities (Angelini, Grande, and Panetta, 2014). In fact, not only do Italy and Spain display the highest systemic exposures, but the systemic sovereign intensity also reaches its highest values in the summer of 2011.

At this stage, it is instructive to compare our results on systemic sovereign risk with those of Ang and Longstaff (2013). First, Ang and Longstaff's (2013) estimated systemic exposures for France, Italy, and Spain are 0.93, 1.71, and 1.51, respectively. Second, their systemic sovereign intensity reaches its peak in the 2008-2009 crisis, while it has much lower values when the crisis evolves into a sovereign debt crisis. Therefore, their estimates seem to reflect the impact of the US crisis on Europe rather than the impact of the Eurozone's debt crisis. This is also suggested by the similar behavior of the sovereign systemic intensities for the US and Europe. This is may be due to the fact that they focus on a much shorter sample, which is dominated for two-thirds by the 2008-2009 crisis. In addition, they consider a much larger number of countries, whereas we focus on a smaller, but systemically important, group of countries.[14]

Moreover, our estimated systemic sovereign intensity is remarkably different from the systemic *bank* intensity presented by Li and Zinna (2013), which is estimated separately on a panel of seven large US and UK banks. Taken together, these results seem to provide a first piece of evidence, which will be complemented with the subsequent analysis, that our estimates well reflect the systemic risk of the Eurozone sovereigns.

As also noted by Li and Zinna (2013), the systemic exposures seem to largely reflect the credit risk of the sovereign, as proxied, for example, by the average five-year CDS spread over the period. We therefore complement the analysis by looking at the *systemic intensity weight* (SIW), *i.e.* $\alpha_i S_t/(\alpha_i S_t + C_{t,i})$, whereby systemic risk is standardized by the total risk of the sovereign, and it is, therefore, comparable across sovereigns with different credit risks. SIW summary statistics are displayed in the bottom panel of Table 2. Interestingly, we find that the ordering of the systemically important banks changes remarkably when moving from the systemic exposures to the SIWs. In fact, the systemic component explains, on average, 66.2% and 69.7% of the credit risk of Germany and France, respectively, but only 48.5% and 44.4% of the credit risk of Italy and Spain, respectively. The strong variability displayed by the SIWs, which range from 0 to almost 100%, is also striking.

Country Credit Risk. Figure 2 shows the country sovereign intensities ($C_{t,i}$) along with the scaled systemic sovereign intensities ($\alpha_i S_t$), which are the building blocks of the SIWs, for each country. First, we note that a small but significant component of the credit risk of Germany is country specific, which supports our identification strategy. However, the country component is generally much lower than the systemic component until the drop in systemic risk following the "Whatever It Takes" speech by Mario Draghi. Moreover, as the tensions become systemic in the summer of 2011, country risk drops to zero, and German credit risk is entirely explained by the systemic component. The evolutions of the systemic and country sovereign intensities of France largely mirror those of Germany, although the French intensities take much higher values. Of further note is that while there is an increase in the country credit risk of Germany at the peak of the 2008-2009 crisis, such an increase is not evident for France.

In contrast, country credit risk is an important, and often dominant, driver of credit risk in Italy and Spain. However, there are also important differences between the two countries.

[14] As mentioned earlier, we also estimated the our model using the Ang and Longstaff (2013) specification such that Germany can only default during a systemic credit event. The estimated exposures using their identification are similar to those estimated using our identification strategy. In addition, the evolution of the systemic intensities is similar. Therefore, the identification strategy does not drive the differing results.

For example, Italy's country credit risk rises in conjunction with the increase in the systemic intensity, in the aftermath of Lehman's bankruptcy. This early increase in country credit risk is specific to the Italian sovereign, as it is not priced into the other country CDS premia. Moreover, the increase in Italian country credit risk during the second phase, starting with the first bailout package for Greece, is limited. At that time Italian credit risk is largely driven by its systemic component. Then, a sudden increase in country credit risk leads the remarkable increase in systemic credit risk at the start of the third phase in the summer of 2011. Country risk and systemic risk then seem to co-move roughly until the time the Greek parliament passes the austerity bill in February 2012. At this time the drop in systemic risk is attenuated, in part, by an increase in country risk. Country credit risk then makes a remarkable downward jump following Mario Draghi's speech, so that the drop in the Italian CDS spreads is driven by both components.

We now turn to the case of Spain. One key difference between Spain and Italy is that during the second phase, Spain's credit risk is equally due to its systemic and country sovereign components. Furthermore, as systemic risk wears off at the beginning of 2011, country sovereign credit risk instead picks up, and this rise is persistent, ending only in September 2011, when systemic risk becomes the main driver of the rise of Spanish CDS spreads. Moreover, the sudden drop in systemic risk in February 2012 is offset by the rise in country credit risk. Therefore, during this event, the remarkable drop in systemic credit risk drives the drop in the CDS premia of Germany and France, but this drop is partly offset in Italy and completely in Spain by an increase in country credit risk. Around the time of Mario Draghi's speech in May 2012, country credit risk is about twice as high as systemic credit risk in Spain. However, similar to Italy, in the aftermath of the second speech by Mario Draghi, both systemic risk and Spanish country risk decrease remarkably in the aftermath of Mario Draghi's second speech.

5.2 Bank Credit Risk

Table 3 presents the estimates of individual bank exposures to systemic and country sovereign risk. We also report the country averages of the bank exposures. Recall that systemic exposure $\alpha_{i,j}$ denotes the ratio of the conditional probability of default of bank (i,j) to that of Germany in the event of a systemic sovereign shock (S_t). The average systemic exposure of Spanish banks is, by far, the largest (4.60), while that of German banks is the lowest (1.63). Also interesting is the fact that, even though Italian banks display average CDS spreads that are similar to those of Spanish banks, the systemic exposure of the average Italian bank is substantially lower (1.95). The average systemic exposure of French banks is also particularly high (2.84).

Nevertheless, riskier banks tend to have higher systemic exposures. For this reason, we again construct the SIW, which is computed as $\alpha_{i,j}S_t/(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$ for banks. It follows that systemic risk, on average, explains the largest fraction of French banks' credit risk

(30%), which can reach a maximum of 81%. Italy is at the other extreme, as systemic risk, on average, only explains 11% of banks' credit risk, reaching a maximum of 39%.[15] Systemic credit risk explains roughly 16% and 21%, respectively, of German and Spanish banks' credit risk.

Table 3 also shows individual banks' exposures to country sovereign credit risk ($\gamma_{i,j}$), denoting the ratio of the conditional probability of default of bank (i, j) to that of the domestic sovereign i in the event of a country-specific sovereign shock ($C_{t,i}$). The average country exposures of German and French banks are larger than unity, as they are respectively 1.60 and 1.74. This indicates a higher probability of defaulting than the domestic sovereign in the event of a country sovereign shock. In contrast, Italian and Spanish banks have roughly the same average country exposures at 0.54 and 0.56, respectively. However, Figure 2 reveals that the German and French country sovereign intensities are much smaller than the Italian and Spanish intensities. Thus, it is natural to wonder what fraction of banks' credit risk is explained by country sovereign risk. We answer to this question by constructing the *country intensity weights*, $CIW = \gamma_{i,j}C_{t,i}/(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$, which therefore complement the analysis of the SIWs. Interestingly, country risk explains, on average, a similar fraction of Spanish (23.6%), Italian (18.4%), and French (17.0%) banks' credit risk, whereas it is only 7.2% of German banks' credit risk.

Taken together, these results show that sovereign credit risk, on average, accounts for roughly 45% of the credit risk of French and Spanish banks, 30% of the credit risk of Italian banks, and 23% of the credit risk of German banks. However, fundamentally the results support our conjecture that banks are exposed to both systemic and country sovereign risk.

Figure 3 shows the decomposition of bank credit risk into its systemic, country, and idiosyncratic components over time (country averages). A few considerations are in order. First, at the start of the 2008-2009 crisis, bank credit risk is largely idiosyncratic. Then, the crisis deteriorates with Lehman's bankruptcy. In response, the European governments introduce system-wide measures to rescue the banking sectors (dotted lines in Figure 3). As a result, in October 2008, sovereign risk explains roughly 50% of banks' credit risk, on average, across countries, ranging from 40% for German banks to 68% for French banks. This evidence, coupled with the visual inspection of Figure 4, which shows the country averages for scaled systemic, scaled country and idiosyncratic intensities, seems to confirm that credit risk is transferred from the banks to the sovereigns with the introduction of the system-wide rescue programmes. In fact, around October 2008, the increase in sovereign risk, as reflected in the systemic intensity in particular, seems to be associated with a drop in the bank-idiosyncratic intensities. This is particularly evident for French, Italian and Spanish banks. In contrast, the idiosyncratic credit risk German banks is still rising when sovereign risk also starts its sudden

[15] Note that this result for Italian banks is largely driven by Intesa Sanpaolo and Unicredit, which display null exposures to systemic risk. The remaining banks display exposures that range from 2.98 and 3.41, which result in SIWs comparable to those of the other European banks.

rise. Overall, our results seem to fit with the timeline of the 2008-2009 crisis suggested by Acharya, Dreschsler, and Schnabl (2013).[16]

An inspection of Figure 3 also highlights the fact that since the announcement of the Greek rescue package, sovereign credit risk captures a substantial and rather stable share of French and Spanish banks' credit risk. In contrast, the fraction of idiosyncratic bank credit risk in Germany and Italy is high throughout the sample. However, for Italian banks, country sovereign credit risk explains a large fraction of banks' credit risk starting as early as October 2008. In contrast, country sovereign credit risk only begins to play a significant role in explaining German and French banks' credit risk in late 2009.

5.3 Cross-Sectional Analysis of Bank Exposures

Thus far, we have presented the estimated individual bank systemic and country exposures to sovereign risk. We now try to relate those exposures to a number of measures that are likely to be important for explaining cross-sectional differences in banks' sovereign exposures. We do this by undertaking a series of cross-sectional regressions.

Bank Size. Indicators of financial institutions' systemic exposures, such as the SRISK,[17], tend to combine the information implied in the probabilities of default with the loss, or capital shortfall, in the event of default. Not surprisingly, the resulting rankings reveal that size is a key determinant of the bank's systemic importance.[18] In fact, the largest institutions generally score also as the most systemically important institutions.

Large banks benefit from "too-big-to-fail" subsidies, which reduce the bank risk and, in turn, imply a lower cost of funding (Laeven, Ratnovski, and Tong, 2014). However, this implicit subsidy can increase the exposure of larger banks to the financial system, thereby increasing their systemic exposure. The introduction of the euro increased the exposure of global (large) European banks to most of the peripheral countries of the Eurozone, and, thus, to the Eurozone tail risk (Noeth and Sengupta, 2012).[19]

[16] Acharya et al (2013) identify three periods. During the first period, sovereign CDS premia remained low, despite the sustained deterioration in bank credit risk. This may reflect the fact that the market did not expect the government to step in or did not fully price in the expected transfer of credit risk in the event of bank bailouts. This period ends in conjunction with the announcement of the first bank bailouts. The second period covers the bank bailouts, and the consequent shift of credit risk from the banks to the sovereign. A high level of comovement between sovereign and bank CDS spreads characterizes the third phase.

[17] SRISK is based on the marginal expected shortfall of Brownlees and Engle (2012) and Acharya, Pedersen, Philippon, and Richardson (2010).

[18] Size also correlates with other standard categories on which the assessment of systemically important institutions is based (Laeven, Ratnovski, and Tong, 2014). Moreover, compared to these other categories, size is readily available and is easy to use. For example, the other categories used by the Basel Committee (BIS, 2013), which include cross-jurisdictional activity, interconnectedness, substitutability, and complexity, are more difficult to access, with some of that data being unknown to the market. As a detailed description of these different indicators is beyond the scope of this study, we refer the reader to the survey of Bisias et al. (2012).

[19] It is also worth emphasizing that, in the presence of a naked CDS ban for sovereign CDSs, investors are

A natural question, therefore, is whether there is a link between bank size and the type of bank credit risk. Put simply, do larger European banks display a larger fraction of systemic (or country) credit risk? In attempting to answer to this question, it is key that bank size is not used as an input in the construction of bank systemic exposure measure. This clearly occurs in our case, as our measures of systemic risk are based on market prices rather than on balance-sheet data. Specifically, we perform cross-sectional regressions of the time-series averages of SIW and CIW on bank size (Table 4).[20]

We measure bank size in terms of the total assets of the bank relative to domestic GDP.[21] Interestingly, we find that bank size is statistically significant at the 5% in the SIW regression, and at the 1% in the CIW regression. Therefore, both fractions of banks' sovereign credit risk – systemic and country specific – increase with bank size, so that larger banks display less idiosyncratic credit risk, as suggested by Laeven, Ratnovski and Tong (2014). In contrast, smaller banks display higher average CDS premia, and their credit risk is largely bank specific.

Holdings of Sovereign Debt. Banks' holdings of domestic and non-domestic European sovereign debt determine their *direct* exposures to sovereign risk (e.g. Bolton and Jeanne, 2011; Acharya, Dreschsler, and Schnabl, 2013; Acharya and Rajan, 2013; and, Gennaioli, Martin, and Rossi, 2013). In contrast, our estimates are extracted from asset prices and should therefore capture the *overall* - direct and indirect - bank's exposure to sovereign risk. Thus, it is worth investigating to what extent our measures correlate with measures of banks' direct exposures to sovereign risk, such as holdings of sovereign debt. Our premise, therefore, is that the SIW should increase in banks' holdings of *non-domestic* sovereign debt, whereas the CIW should increase in banks' holdings of *domestic* sovereign debt.[22] We find strong

buying protection on European banks on the basis that banks and sovereigns are so intimately linked that any increased risk of a sovereign default will increase the value of a bank CDS in a way similar to a sovereign CDS (Financial Times, 2013b). However, investors tend to hedge their exposures using large rather than small bank CDS. In fact, investors' hedging activity, or their bets against the sovereign, were particularly intense in the iTraxx Senior Financial index, which is one of the most liquid European indices encompassing some of the largest banks in the region.

[20]Here we aim to explore the relationship between bank size and the bank type of credit risk. We therefore use the SIW (CIW) instead of the systemic (country) exposures $\alpha_{i,j}$ ($\gamma_{i,j}$). Recall that the SIW and CIW are standardized by the total credit risk of the focal bank, and are therefore readily comparable across banks of different riskiness (see Section 5.2). The systemic exposures, in particular, seem to increase with the credit risk of the bank, so that riskier banks display a higher probability of defaulting in the event of a systemic crisis. Also note that we run the analysis cross sectionally, as the key ingredients of the SIW and CIW are the respective exposures, which are constant over time.

[21]We match the time series averages of the 2008-2013 SIW and CIW with the averages of bank size over the 2007-2012 period to account for the delay with which balance-sheet variables are released to the market. Also note that the results are robust to not standardizing total assets by GDP.

[22]Individual banks' holding of domestic and non-domestic sovereign securities are collected by the EBA as part of the stress-testing and capital exercises that were conducted and published by the EBA. However, the EBA data are reported at infrequent intervals and for only five reporting dates. As noted earlier, this is not a major concern, since we are interested in explaining the cross section of banks' sovereign exposures and the building blocks of the SIW and CIW are $\alpha_{i,j}$ and $\gamma_{i,j}$, which are constants. Specifically, we use the sovereign exposures, i.e. bank holdings of sovereign securities, of the 2011 EBA EU-wide stress test, which were published in July 2011 and refer to the sovereign exposures as of December 31, 2010. Notably, the 2011

statistical support for this hypothesis (Table 4). In economic terms, a one €billion increase in the holdings of domestic (non-domestic) sovereign debt is associated with an increase in the CIW (SIW) by 0.26% (0.16%).

Sovereign Subsidy ("Zero Risk Weight"). Holdings of sovereign debt can determine banks' exposures to sovereign risk through a related channel resulting from the "zero risk weight" regime. More precisely, a "zero risk weight" *de facto* applied to banks' holdings of Eurozone government debt, so that European banks were not required to maintain a capital buffer against their holdings of sovereign debt issued by any EU member state (e.g. Angelini, Grande and Panetta, 2014; Korte and Steffen, 2014). Observers deemed this regime to be an implicit subsidy provided by the sovereigns to the banks, as the banks were required to hold less capital for a given level of risk if they held Eurozone sovereign bonds. An unintended consequence could be that, by incentivizing banks to hold Eurozone sovereign debt, this regime could increasingly link the banks to the outlook not only of the domestic sovereign but also of the Eurozone as a whole. We therefore test whether these domestic and non-domestic sovereign subsidies relate to our estimated systemic and country exposures, CIW and SIW. We follow Korte and Steffen (2014) in measuring the domestic and non-domestic subsidies, by assigning to each holding of sovereign debt the appropriate EBA risk weight, i.e. the risk weight that applies to a corporate bond of comparable rating.[23] We find that both legs of this hypothesis are strongly supported by data, as the domestic subsidy enters with a positive sign in the CIW regression, and the non-domestic subsidy enters with a positive sign in the SIW regression (Table 4).[24]

Expected Government Support. There is also an active stream of literature investigating the link between the expected government support and asset prices (e.g. Noss and Sowerbutts, 2012; Tsesmelidakis and Merton, 2012; and Correa et al., 2014). For example, Correa et al. (2014) find that banks expecting to receive government support display lower stock returns after sovereign rating downgrades. However, this effect is not present when their measure of expected government support is replaced with bank holdings of government debt. This in turn suggests that the expected government support and bank holdings of government debt may reflect different aspects of bank exposures to country sovereign risk. Our hypothesis is

EBA sovereign exposures well represent our sample, as they fall around the sample mid point.

[23]The implicit subsidy is constructed by assigning appropriate risk weights to the sovereign exposures published in the 2011 EBA EU-wide stress test. We refer to Appendix D in Korte and Steffen (2014) for the detailed description of the methodology.

[24]Also note that the domestic subsidy enters with a negative and statistically significant sign in the SIW regression. Thus, the larger the domestic subsidy, the smaller (larger) the fraction of bank credit risk due to systemic (country) sovereign risk is. In contrast, although the coefficient is not statistically significant, the foreign subsidy enters with a positive sign in the CIW regression. This is consistent with the hypothesis that a high non-domestic subsidy may intensify the bank's exposure to the domestic sovereign (Korte and Steffen, 2014). More specifically, in the event that non-domestic sovereign risk materializes, the bank is left undercapitalized and the domestic sovereign will have to bail out the domestic bank. Fundamentally, this mechanism also shows how sovereign risk can be transmitted within the EU member states.

that banks that expect more government support are more closely linked to the fortunes of the domestic sovereign, and therefore more likely to default in the event of a country-specific sovereign credit shock. Put simply, the greater the expected government support, the higher the bank's country exposure ($\gamma_{i,j}$) is.

The expected government support can be measured in a number of ways (IMF, 2014). In this study, we follow the ratings-based approach of Correa et al. (2014), in which the expected government support, i.e. the 'uplift', is measured as the bank's ability to repay its deposit obligations (*all-in-all* rating) minus the bank's intrinsic safety and soundness (*stand-alone* rating).[25,26] The average uplift over the 2007-2012 period for our sample of large European banks tends to decrease with the strength of the bank, while it increases with the strength of the domestic government. This suggests that the market perceives the government support provided by a government that is itself in difficulties as less credible or effective.

We first regress the cross section of bank exposures on the all-in-all credit rating. The estimated coefficient is positive and statistically significant at the 10% level, which indicates that banks with a higher deposit rating, i.e. safer banks, display higher country exposures (Table 5). However, the all-in-all credit rating is composed of the uplift and the bank financial strength rating. For example, a bank with an all-in-all credit rating of 13 and a stand-alone credit rating of 11 benefits from an uplift of 2 notches. Thus, we repeat the regression for each component in turn. We find that the uplift enters the regression with a positive coefficient, which is statistically significant at the 10%. This supports our hypothesis that banks with a higher expected support are more likely to default in the event of a country sovereign shock. In contrast, we find no statistically significant link between the bank financial strength and the country exposure. The results are robust to the inclusion of both components in the regression, with the uplift becoming significant at the 5% level.[27] We then repeat the analysis by replacing the systemic exposure with the CIW as dependent variable. This alternative specification, which is more in line with the regressions presented in Table 4, shifts back the focus on what determines cross-sectional differences in the fraction of bank credit risk that is due to country sovereign risk. The results change considerably (Table 5). In fact, CIW increases with the strength of the bank, while it decreases with the uplift. But, when we include both the strength of the bank and the uplift, we find that only the strength of the bank is significant at the 5%.

[25] In line with Correa et al. (2014), we measure the all-in-all credit rating using Moody's foreign-currency deposit rating, which is assigned on a scale ranging from A to E, and the stand-alone credit rating using the Moody's bank financial strength rating, which is assigned on a scale from Aaa to Ca. The two types of ratings are therefore expressed using different scales with a different number of notches. We therefore first map the deposit-rating scale to the bank financial strength thirteen point scale. We then translate both ratings to the 1-13 numerical scale, such that the numbers increase with the safety of the bank.

[26] One caveat is that the uplift may not only reflect the expected support from the government, but also any potential support from the parent bank. However, given that we only include parent banks in this study, the uplift is a direct measure of the expected government support.

[27] The analysis is based on 20 banks, as we had to exclude one bank for which the rating has been withdrawn.

In sum, these results suggest that banks with a higher expected government support have higher country exposures, while safer banks have a larger fraction of country-specific sovereign credit risk.

5.4 Discussion

A number of academic studies, such as Acharya, Dreschsler, and Schnabl (2013), have focused on the two-way intimate nexus between sovereigns and banks. Shaky bank balance sheets can compromise the solvency of the sovereign, which can, in turn, feed back to the banks' balance sheets (Weidmann, 2013). Ways of breaking this nexus are at the center of an active policy debate (*e.g.* Angelini, Grande, and Panetta, 2014). A natural question, therefore, is the extent to which our first-stage estimates reflect *sovereign* credit risk rather than *bank* credit risk. Clearly, our first-stage estimates of sovereign credit risk can reflect the fragility of the banking sector to some extent (see e.g. Reinhart and Rogoff, 2009). However, a number of factors seem to suggest that our first-stage estimates largely reflect sovereign credit risk and that our second-stage estimates, therefore, capture individual banks' exposures to sovereign risk.

First, in a number of countries, the crisis is caused by the fragility of the sovereign. In other countries, it originates in the banking sector, then compromises the solvency of the sovereign before eventually feeding back to the banks. However, while the fragility of the banks is particularly evident during much of 2008, the subsequent transfer of credit risk from the banks to the sovereign is concentrated in a particularly short period that follows the introduction of the systemic-wide rescue programmes (Acharya, Dreschsler, and Schnabl, 2013). From that point on, the direction of the nexus in the Eurozone goes largely from sovereigns to banks. As a result, roughly 80% of our sample is characterized by sovereign fragility affecting both domestic and non-domestic banks.

Second, our estimates (see Sections 5.1 and 5.2) are generally consistent with the timeline of the 2008-2009 crisis proposed by Acharya, Dreschsler, and Schnabl (2013). Moreover, the evolution of systemic and country sovereign intensities fit with the anecdotal evidence describing the evolution of sovereign risk, and the major political events, in the Eurozone from 2008 through 2013. Furthermore, our estimates of systemic sovereign credit risk are remarkably different from the estimates of systemic *bank* credit risk for the US and UK presented by Li and Zinna (2013), even though they look at a similar time period and use a model specification that closely resembles our first-stage modeling of sovereign risk.

Third, the comparison of bank and sovereign exposures, both systemic and country specific, provides an additional indication that our first-stage estimates largely capture sovereign risk. In fact, individual Italian and Spanish bank exposures to Euro tail risk are generally lower than the exposures of the domestic sovereign. The Italian sovereign systemic exposure is much larger than the exposure of any of the Italian banks, which suggests that the sovereign was the main source of fragility. For Spain, the evidence is mixed, but the Spanish sovereign's systemic exposure is larger than the systemic exposures of the Spanish *largest* banks. Of additional note is that Italian and Spanish banks display exposures to country sovereign credit risk that are less than unity, i.e. lower than the exposure of the domestic sovereign.[28] In contrast, German and French sovereigns have lower exposures to both types of sovereign shocks than the domestic banks, which is in line with the original 'sovereign ceiling' hypothesis (Durbin and Ng, 2005). More fundamentally, these estimates might also reflect the significant exposures of French and German banks to the credit risk from peripheral Europe (Noeth and Sengupta, 2012).

Fourth, our estimates, which are based on the term structure of CDS premia, reveal the market's assessment of banks' exposures to sovereign risk. These exposures can therefore reflect not only the *direct* exposures of individual banks to sovereign risk, resulting from their holdings of European sovereign debt, but also their *indirect* bank exposures. For example, banks with fragile business models might be indirectly exposed to the sovereign debt crisis irrespective of their holdings of sovereign securities. That said, the fact that the shares of bank credit risk resulting from exposure to systemic and country sovereign credit risk are explained, respectively, by banks' holdings of domestic and non-domestic sovereign debt, constitutes possibly the most compelling piece of evidence that our model accurately identifies sovereign credit risk and its components.

Fifth, sovereign credit risk should not be the only source of comovement in banks' credit risk, as banks' fortunes are linked beyond their common exposures to sovereign risk. For example, Kallestrup, Lando, and Murgoci (2013) argue that the bulk of banks' foreign exposures are to the private sector and not to the sovereigns. Clearly, there are also other potential sources of fragility that are common to the banks that might not pertain to the sovereign.[29] This implies that if the first-stage estimation accurately captures sovereign risk instead of bank credit risk, then the bank *idiosyncratic*-intensities of default, $I_{t,i,j}$, displayed in the Internet Appendix, should co-move. We therefore perform a principal component analysis of (the changes in) the bank-idiosyncratic intensities. We do this at the European level, and

[28]We argue that our two-stage procedure enables us to first estimate sovereign risk, and then bank exposures to sovereign risk. In light of the results in Li and Zinna (2013), we would expect that a joint (one-stage) estimation of the model would result in the systemic and country intensities capturing largely bank comovement in credit risk at the national and Eurozone levels, and therefore the estimates would be silent about banks' exposures to sovereign risk. This is because the cross section in the joint estimation would be dominated by banks' CDSs rather than sovereigns' CDSs (i.e. 21 banks versus 4 sovereigns), so that the model will, above all, try to price bank credit risk. In fact, we experimented with a joint estimation of the model and found that the results were substantially different from those of the two-stage estimation. Not only the evolution of the systemic intensity was different but individual bank exposures' to systemic and country intensities were also remarkably higher than the sovereign exposures. Taken together, this evidence offers additional support for our two stage-estimation methodology for quantifying banks' exposures to sovereign risk.

[29]Some standard sources of banks' commonality are, for instance, the repo market, monetary policy, liquidity shocks and regulation (see, e.g., Kashyap and Stein, 2000, 2004; Cetorelli and Goldberg, 2012). We also refer to Brunnermeier (2009), and Eichengreen, Mody, Nedeljkovic and Sarno (2012) for a detailed description of commonalities in banks' own credit risk.

separately at the country level. We find that there is, in fact, substantial comovement in the evolution of bank-idiosyncratic credit risk at the European level and, to an even greater extent, at the country level (see the Internet Appendix). Notably, the resulting principal components behave as level factors, as they load positively on all bank-idiosyncratic intensities. In addition, the plots of the (cumulative sum of the) European bank and country systematic factors present some similarities to, as well as important differences from, the systemic and country sovereign intensities displayed in Figure 2.

In sum, these pieces of empirical evidence seem to support the premise that our model specification and the two-stage model estimation methodology allow us to shed light on banks' exposures to both systemic and country-specific sovereign credit risk.

6 Risk Premia: Components and Term Structures

Expected excess returns to investors for bearing the credit risk on defaultable bonds, or simply default risk premia, are at the heart of the current policy debate. In particular, there is an increasing consensus that estimates of bond risk premia should serve as an input into the monetary policy framework (Stein, 2014). One key advantage of our term-structure model is that based on the estimates we can easily construct the total default risk premia, as well as the risk premia associated with each component of credit risk for different horizons.

6.1 Distress Risk Premia

Investors bear the risk that future arrival rates of the credit events will differ from the current consensus expectation implied in the CDS market. They therefore demand a compensation, in the form of a *distress risk premium*, for being exposed to unexpected changes in the intensity of default. The distress risk premium is widely explored in the credit risk term structure literature (e.g., Pan and Singleton, 2008; Longstaff et al 2011; and, Zinna, 2013).[30] However, that stream of literature generally relies on a single intensity that is assumed to determine the sovereign probability of default, *i.e.*, univariate models of credit risk. In our model, in contrast, the sovereign intensity of default is composed of a systemic component, a country-specific component, and the bank intensity accounts also for an idiosyncratic component. Each component can command a separate risk premium, and each risk premium can display peculiar properties.

The distress risk premium is simply computed as the difference between the default swap

[30] A number of studies instead looks at the jump-at-event risk premium, which compensates the investor for an unexpected jump in price that may take place in conjunction with a credit event that triggers CDS contracts. This risk premium is given by the distance between the risk-neutral and the objective arrival rates of the credit event (Driessen, 2005). However, in modeling the term structure of CDS premia, we can only extract the risk-neutral intensity of default. We would need additional data on the actual probability of default to estimate the objective intensity of default.

spread priced under the risk-neutral probability measure (CDS) and under the objective measure ($\text{CDS}^{\mathbb{P}}$). The pricing of both CDS and $\text{CDS}^{\mathbb{P}}$ is based on equation (3), which depends on the total intensity of equation (4) for sovereigns and on the total intensity of equation (7) for banks. More specifically, the difference is that the default probability driving the objective CDS price is implied in the intensities defined under the objective probability of equations (9) and (10) for sovereigns, and equations (9)-(11) for banks. In other words, under the essentially affine specification of the market price of risk, the $\text{CDS}^{\mathbb{P}}$ price is obtained by replacing $\kappa^{\mathbb{Q}}$ and $\kappa_i^{\mathbb{Q}}$ (and also $\kappa_{i,j}^{\mathbb{Q}}$) with $\kappa^{\mathbb{P}}$ and $\kappa_i^{\mathbb{P}}$ (and also $\kappa_{i,j}^{\mathbb{P}}$), respectively, when pricing sovereign (bank) CDS premia.

A similar reasoning applies when the objective is to identify the separate components of the risk premium. More specifically, in order to quantify the magnitude of each risk-premium component, we set the relevant market price of risk at zero.[31] Take, for example, the systemic risk premium, which consists of replacing $\kappa^{\mathbb{Q}}$ with $\kappa^{\mathbb{P}}$ when pricing the CDS contract. We can then compute the country and bank-idiosyncratic risk premia in similar ways. It is then standard to present the contribution of the risk premium to the spread (e.g. Pan and Singleton, 2008). For example, the percentage contribution of the *total risk premium* to the spread with maturity M is defined as $CRP(M) = (CDS(M) - CDS(M)^{\mathbb{P}})/CDS(M)$. The percentage contributions of risk-premia components to the spread are computed in a similar way by using the pseudo-objective spread associated with the focal component. The term structure of the CRPs, and of their components, are then easily obtained by varying the maturity M. In sum, when the risk-neutral CDS price is larger than the pseudo-objective price $\text{CDS}^{\mathbb{P}}$, the buyer of protection is willing to pay a premium for holding the CDS contract.

6.2 Empirical Estimates

Table 6 presents summary statistics for the term structure of the sovereign distress risk premia components. We find that the percentage contribution of the total risk premium to the spread (CRP) decreases with the credit risk of the sovereign. In fact, the CRPs of Germany and France are higher than those of Italy and Spain. In addition, the CRPs increase with the maturity. For example, for Germany, the risk premium explains roughly 68% of the one-year spread, and almost the entirety of the ten-year spread. In contrast, for Spain, the one-year CRP is about 47% and the ten-year is about 87%. Regardless of the sovereign, the term structures of the CRPs slope upward.

However, the analysis of the CRP components reveals that the behaviors of the systemic (SCRP) and country (CCRP) risk premia are remarkably different. In fact, the SCRPs display hump-shaped term structures, while the CCRPs term structures slope upward. This suggests

[31]The methodology behind this decomposition closely follows Li and Zinna (2014). We refer the reader to the detailed description of the risk premia algebra presented in their Internet Appendix. Their methodology is easily extended to our three-factor model, which determine the pricing of bank credit risk.

that shorter-term contracts are particularly informative on Euro tail risk. This is because CDS term structures tend to invert during periods of market turmoil, so that shorter-term contracts react more to Euro tail risk – and they do so more quickly – than longer-term contracts. Specifically, one-year SCRPs for Germany and France are roughly twice as large as the respective CCRPs, while the ten-year SCRPs are substantially lower than the respective CCRPs. Of particular interest is also the fact that although the CRP is rather stable over time, its components display substantial time variation, which suggests that the SCRPs and CCRPs tend to move in opposite directions.

Table 7 reports bank distress risk premia in terms of country averages. Banks' CRPs are generally lower than sovereign CRPs, and this difference is particularly large for German banks. Furthermore, the slope of the banks' CRP is steeper than the slope of sovereigns' CRPs. This result may be due to the fact the idiosyncratic risk premia (ICRP) also display upward-sloping term structures, thereby reinforcing the effect of the country risk premia, which also show upward-sloping term structures. In contrast, similar to sovereign SCRPs, the term structures of bank SCRPs are hump shaped.

In sum, the properties of the risk premia components are remarkably different. Of particular interest is the systemic risk premium, as its hump-shaped term structure suggests that Eurozone tail risk is largely priced into short- to medium-term CDS contracts. This implies that the estimates of the SIWs might represent an upper boundary. In fact, the decomposition of the CDS spreads for different maturities shows that the importance of the systemic component decreases with the maturity. For example, while the Italian sovereign SIW is 48%, the contributions of systemic risk to the 1-, 3-, 5- and 10-year spreads are 44%, 37%, 28%, and 18%, respectively. Similar results hold for the other sovereigns. In sum, the fraction of CDS spreads due to Euro tail risk, or sovereign systemic risk, displays a downward-sloping term structure. This indicates that the market expects the risk-neutral (or risk-adjusted) probability of a systemic sovereign event, relative to that of a country event, to be higher in the short to medium term.

7 Conclusions

The primary goal of this paper is to quantify, by only using information embedded in CDS data, individual exposures of large European banks to systemic and country-specific sovereign credit risk. Thus, the focus is on what the CDS market tells us about banks' exposures to sovereign risk. We estimate the model in two stages. In the first stage, we estimate the probability of joint defaults of large Eurozone sovereigns (systemic risk) and the probability of sovereign-specific defaults (country risk) for the 2008-2013 period. We find that sovereign systemic credit risk reaches its peak in late 2011 and then wears off in 2012 following Draghi's speeches and the consequent introduction of the Outright Monetary Transactions. Spain and

Italy are the countries most exposed to systemic risk, but systemic risk explains most of the German and French credit risk. It is worth pointing out that part of German credit risk is country specific, which supports our identification strategy.

In the second stage, we quantify each bank's exposure to sovereign risk based on CDS premia. Notably, we find strong evidence that not only European banks are exposed to sovereign risk, but also that they are exposed to both types (systemic and country specific) of sovereign risk. Spanish banks display the highest exposures to systemic sovereign risk. They are followed by French, Italian, and German banks. However, Spanish and Italian banks display lower exposures to systemic risk than their respective sovereigns, which highlights the sovereign nature of the crisis, and the pivotal role of the Italian and Spanish sovereigns. In contrast, the significant exposures of French and German banks to systemic sovereign risk, or Euro tail risk, might reflect their large international exposures (Noeth and Sengupta, 2012). Overall, sovereign credit risk accounts for roughly 45% of French and Spanish bank credit risk, 30% of Italian bank credit risk, and 23% of German bank credit risk, on average, over the sample. However, the share of bank credit risk arising from the sovereign risk components varies significantly over time.

There are significant cross-sectional differences in banks' individual exposures to systemic and country sovereign risk. Therefore, it is important to examine whether these estimated banks' sovereign exposures relate to banks' *direct* exposures to sovereign risk, but also to bank size, and expected government support. We find that the share of bank credit risk that is due to sovereign risk increases with bank size. In contrast, smaller banks display a higher credit risk that is largely bank specific. Moreover, the fraction of banks' credit risk due to their exposures to systemic (country-specific) sovereign credit risk co-moves with their holdings of Eurozone (domestic) sovereign debt. Furthermore, the higher the expected level of government support, the higher the probability that the bank defaults as a country-specific sovereign shock arrives.

These results also bear important policy implications. In particular, it is important to complement the information obtained from measures of direct bank exposures to sovereign risk, such as holdings of sovereign debt, with measures extracted from asset prices, as the latter might also reflect banks' indirect exposures to sovereign risk resulting, for example, from weak bank business models. One caveat is that our results apply to a small group of systemically important European banks. However, Europe serves as an excellent laboratory for examining banks' exposures to sovereign risk.

We complete the analysis by assessing the properties of the distress risk premia, which compensate investors for unexpected changes in the default intensity. These risk premia are also at the center of the policy debate (Stein, 2014). We find that the contribution of the distress risk premia to the sovereign spreads is particularly high and that it decreases with the credit risk of the sovereign. Moreover, it displays an upward-sloping term structure, so that longer-term CDSs largely reflect investors' aversion to unexpected changes in default risk, rather than the objective probability of default of the sovereign. However, the behaviors of the components of the distress risk premia are remarkably different. In fact, while the term structure of the systemic risk premia is hump shaped, the term structure of the country risk premia slopes upward. This evidence partly explains why we find that the fraction of the CDS spreads due to systemic sovereign risk decreases with maturity. This, in turn, indicates that short- to medium-term CDS contracts are more informative than longer-term CDS contracts with regard to the evolution of Euro sovereign tail risk. This result, therefore, lends support to the choice of the ECB to tackle Eurozone systemic risk, or the fears of reversibility of the euro, by focusing the Outright Monetary Transactions on government-issued bonds with short maturities.

A Appendix: Pricing Credit Default Swaps

The pricing of sovereign CDS premia is based on the two-factor pricing models of Ang and Longstaff (2013) and Li and Zinna (2013). Therefore, we refer the reader to those studies. In this Appendix, we present the pricing of bank CDS premia, which is instead new, as it is based on a three-factor pricing model.

Assume that we have a risk-free rate r_t, such that the zero-coupon bond, $D(M)$, with maturity M is priced by:

$$D(M) = E^{\mathbb{Q}}\left[\exp\left(-\int_t^{t+M} r_t dt\right)\right]. \tag{A.1}$$

Given the specification for the default intensity, $\lambda_{i,j,t} = \alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j}$, the dynamics of equations (6), (5), and (8), assuming that r_t and $\lambda_{i,t}$ are independent, and the loss rate $L^{\mathbb{Q}} = 1 - R^{\mathbb{Q}}$, it follows that the price of the CDS spread for bank j located in country i is:

$$CDS_{i,j}(t,T) = L^{\mathbb{Q}} \frac{E^{\mathbb{Q}}\Big[\int_t^{t+M} D(s-t)\lambda_{i,j,s}\exp\Big(-\int_t^s \lambda_{i,j,u}du\Big)ds\Big]}{E^{\mathbb{Q}}\Big[\int_t^{t+M} D(s-t)\exp\Big(-\int_t^s \lambda_{i,j,u}du\Big)ds\Big]}. \tag{A.2}$$

As the states of equations (6), (5) and (8) follow square-root processes, the transform approach proposed by Duffie, Pan, and Singleton (2000) can be used to analytically solve the expectations in equation (3). Also assuming a constant risk free rate, we end up with:

$$CDS_{i,j}(t,T) = L^{\mathbb{Q}} \frac{\int_t^{t+M}\Big(\widetilde{\mathbf{I}}(s,S_s,C_{s,i},I_{s,i,j}) + \alpha_{i,j}\widetilde{\mathbf{C}}(s,S_s,C_{s,i},I_{s,i,j}) + \gamma_{i,j}\widetilde{\mathbf{S}}(s,S_s,C_{s,i},I_{s,i,j})\Big)ds}{\int_t^{t+M}\Big(\mathbf{C}(s,S_s)\mathbf{A}(s,C_{s,i})\mathbf{B}(s,I_{s,i,j}\Big)ds}, \tag{A.3}$$

where

$$\begin{aligned}
\widetilde{\mathbf{I}}(s,S_s,C_{s,i},I_{s,i,j}) &= \mathbf{C}(s,S_s)\mathbf{A}(s,C_{s,i})\mathbf{S}(s,I_{s,i,j}), && \text{(A.4)}\\
\widetilde{\mathbf{C}}(s,S_s,C_{s,i},I_{s,i,j}) &= \mathbf{C}(s,S_s)\mathbf{B}(s,I_{s,i,j})\mathbf{H}(s,C_{s,i}), && \text{(A.5)}\\
\widetilde{\mathbf{S}}(s,S_s,C_{s,i},I_{s,i,j}) &= \mathbf{A}(s,C_{s,i})\mathbf{B}(s,I_{s,i,j})\mathbf{F}(s,S_s), && \text{(A.6)}
\end{aligned}$$

$$\begin{aligned}
\mathbf{B}(s,I_{s,i,j}) &= \mathbf{B}_1(s)\exp(\mathbf{B}_2(s)I_{s,i,j}), && \text{(A.7)}\\
\mathbf{A}(s,C_{s,i}) &= \mathbf{A}_1(s)\exp(\mathbf{A}_2(s)C_{s,i}), && \text{(A.8)}\\
\mathbf{C}(s,S_s) &= \mathbf{C}_1(s)\exp(\mathbf{C}_2(s)S_s), && \text{(A.9)}\\
& && \text{(A.10)}
\end{aligned}$$

$$
\begin{aligned}
\mathbf{S}(s, I_{s,i,j}) &= (\mathbf{S}_1(s) + \mathbf{S}_2(s) I_{s,i,j}) \exp(\mathbf{B}_2(s) I_{s,i,j}), && \text{(A.11)} \\
\mathbf{H}(s, C_{s,i}) &= (\mathbf{H}_1(s) + \mathbf{H}_2(s) C_{s,i}) \exp(\mathbf{A}_2(s) C_{s,i}), && \text{(A.12)} \\
\mathbf{F}(s, S_s) &= (\mathbf{F}_1(s) + \mathbf{H}_2(s) S_s) \exp(\mathbf{F}_2(s) S_s), && \text{(A.13)}
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{B}_1(s) &= \exp\left(\frac{\eta_{i,j}(\kappa_{i,j}^{\mathbb{Q}} + \phi)s}{\sigma_{i,j}^2}\right) \left(\frac{1-\theta}{1-\theta e^{\phi s}}\right)^{2\eta_{i,j}/\sigma_{i,j}^2}, && \text{(A.14)} \\
\mathbf{B}_2(s) &= \frac{\kappa_{i,j}^{\mathbb{Q}} - \phi}{\sigma_{i,j}^2} + \frac{2\phi}{\sigma_{i,j}^2(1-\theta e^{\phi s})}, && \text{(A.15)}
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{A}_1(s) &= \exp\left(\frac{\eta_j(\kappa_j^{\mathbb{Q}} + \psi)s}{\sigma_j^2}\right) \left(\frac{1-v}{1-v e^{\psi s}}\right)^{2\eta_j/\sigma_j^2}, && \text{(A.16)} \\
\mathbf{A}_2(s) &= \frac{\kappa_j^{\mathbb{Q}} - \psi}{\sigma_j^2} + \frac{2\psi}{\sigma_j^2(1-v e^{\psi s})}, && \text{(A.17)}
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{C}_1(s) &= \exp\left(\frac{\eta(\kappa^{\mathbb{Q}} + \psi)s}{\sigma^2}\right) \left(\frac{1-v}{1-v e^{\psi s}}\right)^{2\eta/\sigma^2}, && \text{(A.18)} \\
\mathbf{C}_2(s) &= \frac{\kappa^{\mathbb{Q}} - \psi}{\sigma^2} + \frac{2\psi}{\sigma^2(1-v e^{\psi s})}, && \text{(A.19)}
\end{aligned}
$$

$$
\begin{aligned}
S_1(s) &= \frac{\eta_{i,j}}{\phi}(e^{\phi s} - 1) \exp\left(\frac{\eta_{i,j}(\kappa_{i,j}^{\mathbb{Q}} + \phi)s}{\sigma_{i,j}^2}\right) \left(\frac{1-\theta}{1-\theta e^{\phi s}}\right)^{2\eta_{i,j}/\sigma_{i,j}^2+1}, && \text{(A.20)} \\
S_2(s) &= \exp\left(\frac{\eta_{i,j}(\kappa_{i,j}^{\mathbb{Q}} + \phi)s}{\sigma_{i,j}^2} + \phi s\right) \left(\frac{1-\theta}{1-\theta e^{\phi s}}\right)^{2\eta_j/\sigma_{i,j}^2+2}, && \text{(A.21)}
\end{aligned}
$$

$$
\begin{aligned}
H_1(s) &= \frac{\eta_j}{\psi}(e^{\psi s} - 1) \exp\left(\frac{\eta_j(\kappa_j^{\mathbb{Q}} + \psi)s}{\sigma_j^2}\right) \left(\frac{1-v}{1-v e^{\psi s}}\right)^{2\eta_j/\sigma_j^2+1}, && \text{(A.22)} \\
H_2(s) &= \exp\left(\frac{\eta_j(\kappa_j^{\mathbb{Q}} + \psi)s}{\sigma_j^2} + \psi s\right) \left(\frac{1-v}{1-v e^{\psi s}}\right)^{2\eta_j/\sigma_j^2+2}, && \text{(A.23)}
\end{aligned}
$$

$$
\begin{aligned}
F_1(s) &= \frac{\eta}{\xi}(e^{\xi s}-1)\exp\left(\frac{\eta(\kappa^{\mathbb{Q}}+\xi)s}{\sigma^2}\right)\left(\frac{1-u}{1-ue^{\xi s}}\right)^{2\eta/\sigma^2+1}, && \text{(A.24)}\\
F_2(s) &= \exp\left(\frac{\eta(\kappa^{\mathbb{Q}}+\xi)s}{\sigma^2}+\xi s\right)\left(\frac{1-u}{1-ue^{\xi s}}\right)^{2\eta/\sigma^2+2}, && \text{(A.25)}
\end{aligned}
$$

$$
\begin{aligned}
\phi &= \sqrt{\left(\kappa_{i,j}^{\mathbb{Q}}\right)^2+2\sigma_{i,j}^2}, && \text{(A.26)}\\
\psi &= \sqrt{\left(\kappa_{j}^{\mathbb{Q}}\right)^2+2\alpha_{i,j}\sigma_{j}^2}, && \text{(A.27)}\\
\xi &= \sqrt{\left(\kappa^{\mathbb{Q}}\right)^2+2\gamma_{i,j}\sigma^2}, && \text{(A.28)}
\end{aligned}
$$

$$
\begin{aligned}
\theta &= (\kappa_{i,j}^{\mathbb{Q}}+\phi)/(\kappa_{i,j}^{\mathbb{Q}}-\phi), && \text{(A.29)}\\
v &= (\kappa_{j}^{\mathbb{Q}}+\psi)/(\kappa_{j}^{\mathbb{Q}}-\psi), && \text{(A.30)}\\
u &= (\kappa^{\mathbb{Q}}+\xi)/(\kappa^{\mathbb{Q}}-\xi). && \text{(A.31)}
\end{aligned}
$$

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Table 1: **Summary Statistics**

Name	ID	Mean	StDev	Min	Med	Max	AC(1)	nobs.
Germany	GER	43	26	5	39	108	0.979	311
Deutsche Bank AG	DB	118	40	52	106	287	0.917	311
Commerzbank AG	CB	145	68	53	134	364	0.961	311
Deutsche Zentral-Genossenschaftsbank	DZ	112	27	52	109	190	0.927	311
Landesbank Baden-Wuerttemberg	LBW	132	56	48	118	320	0.968	311
Bayerische Landesbank	BYLAN	129	56	60	110	338	0.971	311
Norddeutsche Landesbank Girozentrale	NDB	135	46	50	121	320	0.959	286
HSH Nordbank AG	HSH	206	63	102	191	379	0.949	286
France	FRA	80	57	7	71	247	0.984	311
BNP Paribas SA	BNP	122	67	35	103	352	0.968	311
Crèdit Agricole	CA	152	72	48	137	383	0.961	311
Sociètè Gènèrale SA	SG	158	85	40	131	417	0.964	311
Natixis	NTX	185	62	55	169	335	0.945	311
Italy	ITA	213	141	25	185	577	0.982	311
Intesa Sanpaolo SpA	ISP	199	138	34	151	572	0.982	311
UniCredit SpA	UI	226	144	46	180	648	0.979	311
Banca Monte dei Paschi di Siena	MPS	303	228	55	215	878	0.987	311
Banco Popolare Societa Cooperativa	BP	329	217	69	266	951	0.982	311
Unione di Banche Italiane	UBI	218	144	36	183	643	0.981	311
Spain	ESP	221	143	24	225	617	0.984	311
Banco Santander SA	BST	201	106	49	189	484	0.973	311
Banco Bilbao Vizcaya Argentaria, SA	BBVA	211	113	47	211	504	0.975	311
Caja de Ahorros y Pensiones	BCXA	232	83	83	235	450	0.961	299
Banco Popular Españ ol SA	BPE	401	212	92	348	926	0.983	291
Banco de Sabadell, SA	BSB	382	195	124	335	833	0.984	299

The table reports summary statistics for the five-year CDS spreads for the sovereigns and the indicated banks. Specifically, we report the time series mean (Mean); standard deviation (StDev); minimum (Min); maximum (Max); first-order autocorrelation coefficient (AC(1)); and number of observations (nobs). We also report the sovereign and bank identifiers (ID) used in the subsequent tables. The sample consists of weekly observations from January 9, 2008 to December 18, 2013. Sources: CMA.

Table 2: **Systemic and Country Intensities' Parameter Estimates**

Panel A: Systemic Intensity (S_t)

η	$\kappa^{\mathbb{P}}$	σ	$k_i^{\mathbb{Q}}$
0	1.33	0.16	-0.48
[0.00;0.00]	[0.33;2.35]	-	[-0.50;-0.46]

Panel B: Country Intensities (C_t)

	η_i	$\kappa_i^{\mathbb{P}}$	σ_i	$k_i^{\mathbb{Q}}$	σ_ϵ^i	α_i
GER	0.1	1.43	0.1	-0.69	2.01	1
	[0.07;0.12]	[0.33;2.58]	[0.09;0.10]	[-0.70;-0.67]	[1.96;2.05]	-
FRA	0.4	0.99	0.11	-0.66	1.62	2.56
	[0.38;0.43]	[0.25;1.70]	[0.11;0.11]	[-0.67;-0.65]	[1.58;1.66]	[2.50;2.63]
ITA	6.19	0.49	0.18	-0.41	2.15	5.96
	[5.93;6.45]	[0.11;0.89]	[0.18;0.18]	[-0.42;-0.40]	[2.11;2.20]	[5.75;6.18]
ESP	7.76	0.39	0.18	-0.3	1.76	6.01
	[7.52;8.01]	[0.10;0.70]	[0.17;0.18]	[-0.30;-0.29]	[1.73;1.80]	[5.79;6.23]

Panel C: Systemic Intensity Weights (SIW)

	Mean	Med.	SDev.	Min	Max	AC(1)
GER	66.2	83.1	33.0	1.4	99.4	0.978
FRA	69.7	87.7	34.3	1.6	99.1	0.980
ITA	48.5	58.9	28.8	0.4	93.2	0.981
ESP	44.4	47.0	30.1	0.3	94.8	0.985

The table reports posterior means and 95% credible intervals (in squared brackets) for the parameter estimates resulting from step-one estimation on sovereign CDSs. The top panel presents the parameters driving the dynamics of S_t (*Systemic Intensity*), whereas the middle panel presents the parameters driving the dynamics of $C_{t,i}$ (*Country Intensities*). The bottom panel reports the summary statistics of $\alpha_i S_t/(\alpha_i S_t+C_{t,i})$ (*Systemic Intensity Weights*). The estimation is performed using the Bayesian algorithm described in Section 4.3, and is based on weekly data from January 9, 2008, to December 18, 2013. The η, η_i, σ_ϵ, and $\sigma_{\epsilon,i}$ parameters are presented in basis points, while the systemic intensity weights are presented as percentages.

Table 3: **Systemic and Country Intensity Weights**

	Panel A: German Banks									
		SIW					CIW			
	$\alpha_{i,j}$	Mean	SDev	Min	Max	$\gamma_{i,j}$	Mean	SDev	Min	Max
DB	1.20	17.3	13.1	0.1	67.2	1.83	12.3	6.1	0.2	87.2
CB	2.32	26.1	23.7	0.2	72.9	2.38	7.9	6.7	0.3	25.8
DZ	1.42	17.3	9.9	0.3	63.5	1.77	9.3	4.2	0.3	39.1
LBW	2.47	20.3	16.0	0.5	61.3	1.96	9.2	3.9	0.2	39.9
BYLAN	1.57	13.0	11.0	0.2	50.4	1.42	8.7	2.8	0.1	52.6
NDB	1.18	9.5	8.4	0.1	23.2	0.03	0.1	0.0	0.0	0.2
HSH	1.24	8.0	3.0	0.1	41.1	1.85	2.9	1.8	0.2	13.4
Avg	1.63	15.9	12.2	0.2	54.2	1.60	7.2	3.6	0.2	36.9
	Panel B: French Banks									
		SIW					CIW			
	$\alpha_{i,j}$	Mean	SDev	Min	Max	$\gamma_{i,j}$	Mean	SDev	Min	Max
BNP	2.37	34.2	36.3	0.4	80.9	1.57	20.3	11.0	0.3	71.3
CA	2.70	30.3	26.6	0.3	83.6	1.99	19.8	12.2	0.3	82.1
SG	3.08	31.9	32.7	0.3	79.8	1.91	17.7	9.0	0.3	79.9
NTX	3.23	22.9	12.6	0.3	80.1	1.51	10.2	6.8	0.1	58.1
Avg	2.84	29.8	27.0	0.3	81.1	1.74	17.0	9.8	0.3	72.9
	Panel C: Italian Banks									
		SIW					CIW			
	$\alpha_{i,j}$	Mean	SDev	Min	Max	$\gamma_{i,j}$	Mean	SDev	Min	Max
ISP	0.00	0.0	0.0	0.0	0.0	0.77	34.1	35.5	1.4	90.9
UI	0.00	0.0	0.0	0.0	0.0	0.91	31.9	31.0	1.2	95.5
MPS	3.41	22.6	17.3	0.1	66.9	0.48	13.7	13.7	0.5	38.9
BP	3.36	14.1	11.8	0.1	60.3	0.51	11.0	11.3	0.4	28.0
UBI	2.98	21.7	20.5	0.1	69.9	0.04	1.6	1.5	0.1	5.2
Avg	1.95	11.7	9.9	0.0	39.4	0.54	18.4	18.6	0.7	51.7
	Panel D: Spanish Banks									
		SIW					CIW			
	$\alpha_{i,j}$	Mean	SDev	Min	Max	$\gamma_{i,j}$	Mean	SDev	Min	Max
BST	3.98	27.6	25.5	0.2	63.4	0.54	32.6	38.1	0.4	69.2
BBVA	4.31	28.9	26.8	0.2	69.4	0.64	36.6	38.9	0.6	84.0
BCXA	2.42	12.5	9.1	0.1	68.0	0.11	5.3	5.0	0.1	20.3
BPE	5.96	16.8	18.1	0.1	46.2	0.74	20.3	24.1	0.3	42.4
BSB	6.32	17.8	18.4	0.1	55.9	0.79	23.4	27.0	0.5	65.5
Avg	4.60	20.7	19.6	0.1	60.6	0.56	23.6	26.6	0.4	56.3

This table reports the individual bank systemic ($\alpha_{i,j}$) and country ($\gamma_{i,j}$) exposures, as well as the summary statistics of the systemic ($SIW = \alpha_{i,j}S_t/(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$) and country ($CIW = \gamma_{i,j}C_{t,i}/(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$) intensity weights. Avg. denotes the averages by country groups. The systemic and country intensity weights are displayed as percentages.

Table 4: **Determinants of Systemic and Country Intensity Weights**

	Panel A: SIW				
	(1)	(2)	(3)	(4)	(5)
Size	0.179^b				
(in %)	(0.0836)				
For.Exp.		0.158^b			
(in €bn)		(0.0716)			
For. Sub.			0.602^b		
(in €bn)			(0.275)		
Dom. Exp.				-0.0977	
(in €bn)				(0.134)	
Dom. Sub.					-1.134^a
(in €bn)					(0.546)
Con.	14.11^a	16.04^a	15.74^a	21.96^a	25.10^a
	(2.957)	(2.329)	(2.416)	(4.738)	(3.581)
Obs.	21	21	21	21	21
R^2(%)	19.5	20.4	20.1	2.7	18.5
	Panel B: CIW				
	(1)	(2)	(3)	(4)	(5)
Size	0.278^a				
(in %)	(0.0837)				
For.Exp.		0.0745			
(in €bn)		(0.0890)			
For. Sub.			0.289		
(in €bn)			(0.341)		
Dom. Exp.				0.262^a	
(in €bn)				(0.141)	
Dom. Sub.					1.472^b
(in €bn)					(0.594)
Con.	8.621^a	14.67^a	14.51^a	7.757	7.945^a
	(2.962)	(2.896)	(2.998)	(4.994)	(3.896)
Obs.	21	21	21	21	21
R^2(%)	36.7	3.6	3.6	15.3	24.4

Panel A: SIW (Panel B: CIW) reports the cross-sectional regressions of the bank mean systemic (country) intensity weights on several measures of banks' exposures to sovereign risk. These measures include: bank size, measured in terms of total assets relative to country GDP (in %); individual bank holdings of domestic (Dom.Exp.) and non-domestic (For.Exp.) sovereign securities, measured in € billions; and domestic (Dom.Sub.) and non-domestic (For.Sub.) sovereign subsidies, measured in € billions. The holdings of sovereign securities were published by the EBA as a result of the 2011 stress tests. The sovereign subsidy is constructed as in Korte and Steffen (2014) by assigning appropriate weights to each holding of sovereign debt. a, b, and c denote the 1-, 5-, and 10-percent significance levels, respectively. Sources: Capital IQ and European Banking Authority (http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2011/results).

Table 5: **Expected Government Support and Bank Exposures to Country Risk**

	$\gamma_{i,j}$				CIW			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
All-in-all CR	0.215^c				2.243			
	(0.123)				(1.983)			
Stand-alone CR		-0.0227		0.172		4.615^a		3.626^b
		(0.101)		(0.122)		(1.113)		(1.511)
Uplift			0.203^c	0.339^b			-4.604^a	-1.724
			(0.109)	(0.143)			(1.476)	(1.778)
Contant	-0.719	1.337^c	0.767^b	-0.680	-3.290	-14.80^c	25.99^a	-4.551
	(1.099)	(0.704)	(0.268)	(1.060)	(17.71)	(7.778)	(3.643)	(13.14)
Obs.	20	20	20	20	20	20	20	20
$R^2(\%)$	14.5	0.3	16.2	24.9	6.6	48.8	35.1	51.5

This table reports the cross-sectional regressions of banks' exposures to country default risk ($\gamma_{i,j}$) on the left panel, and the mean country intensity weight, $CIW = \gamma_{i,j}C_{t,i}/(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$ on the right panel, on several measures. These measures include: the bank's ability to repay its deposit obligations, i.e. Moody's foreign-currency deposit rating (*All-in-all CR*); the bank's intrinsic safety and soundness, i.e. Moody's bank financial strength rating (*Stand-alone CR*); and the expected level of government support, which is measured as the difference between foreign-currency deposit rating and the bank financial strength rating (Uplift). Foreign-currency deposit ratings are mapped from the original BCA scale to the BFSR scale. The BCA is then converted into a numerical scale ranging from 1, indicating the lowest quality, to 13, indicating the highest quality. This methodology closely follows Correa et al. (2014). a, b, and c denote the 1-, 5-, and 10-percent significance levels, respectively. Source: Bloomberg.

Table 6: **Term Structure of Sovereign Risk Premia Components**

Panel A: Germany

	Total				Systemic				Country			
	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr
Mean	68	92	97	99	42	54	51	43	26	38	46	56
Sdev	2	1	1	0	22	29	30	28	24	31	31	29
Min	66	90	96	98	1	1	1	0	1	1	2	5
Max	71	94	98	100	65	89	94	93	71	94	98	99

Panel B: France

	Total				Systemic				Country			
	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr
Mean	65	90	95	98	44	56	50	34	20	34	45	64
Sdev	1	1	1	1	22	30	30	23	22	31	31	24
Min	63	88	94	97	1	1	0	0	1	3	7	25
Max	65	91	97	99	64	86	87	71	63	90	97	99

Panel C: Italy

	Total				Systemic				Country			
	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr
Mean	52	78	86	91	30	35	28	17	22	43	58	75
Sdev	6	3	2	1	17	21	17	12	12	18	17	11
Min	43	71	79	88	0	0	0	0	6	17	31	56
Max	61	83	88	92	54	65	55	37	42	73	85	92

Panel D: Spain

	Total				Systemic				Country			
	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr	1yr	3yr	5yr	10yr
Mean	47	72	80	87	28	33	28	17	19	38	52	70
Sdev	8	5	3	2	18	22	19	13	10	17	17	12
Min	34	64	71	81	0	0	0	0	3	8	15	37
Max	61	83	87	89	58	74	71	52	34	63	77	87

This table reports summary statistics for the term structure of the percentage contributions of distress risk premia, and their components to the 1-, 3-, 5-, and 10-year sovereign CDS spreads. The left panels denote the risk premia induced by the total default intensity ($\alpha_i S_t + C_{t,i}$); the middle panels denote the risk premia induced by the scaled systemic default intensity ($\alpha_i S_t$); and the right panels denote the risk premia induced by the country default intensity ($C_{t,i}$).

Table 7: **Term Structure of Bank Risk Premia Components by Country Averages**

Panel A: German Banks

	Total				Systemic				Country				Idiosyncratic			
	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y
Mean	33	56	68	76	11	18	20	17	6	12	17	21	15	26	29	37
Sdev	6	7	7	5	9	14	16	14	6	11	14	15	4	7	9	10
Min	23	43	54	66	0	0	0	0	0	1	1	2	7	12	13	19
Max	47	70	80	85	34	49	54	50	25	41	51	53	21	39	48	58

Panel B: French Banks

	Total				Systemic				Country				Idiosyncratic			
	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y
Mean	47	74	84	89	20	27	25	18	12	24	32	39	15	23	26	32
Sdev	7	7	6	4	15	20	19	14	12	20	24	22	7	13	15	16
Min	33	58	70	81	0	0	0	0	0	2	4	10	3	6	7	11
Max	61	85	92	95	51	65	62	48	45	69	79	79	29	51	59	65

Panel C: Italian Banks

	Total				Systemic				Country				Idiosyncratic			
	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y
Mean	30	55	68	80	8	12	12	8	9	21	31	46	12	21	24	25
Sdev	7	9	7	4	7	9	9	6	5	8	9	9	4	7	9	8
Min	20	41	54	70	0	0	0	0	1	5	11	27	2	4	6	9
Max	47	74	83	88	26	35	33	21	22	42	53	67	18	34	41	41

Panel D: Spanish Banks

	Total				Systemic				Country				Idiosyncratic			
	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y	1y	3y	5y	10y
Mean	36	61	72	81	15	20	19	13	9	18	25	39	13	22	26	29
Sdev	6	6	4	3	11	15	15	10	5	10	12	13	5	9	11	11
Min	27	51	63	75	0	0	0	0	1	3	5	14	4	7	8	11
Max	51	75	81	87	40	54	51	38	20	39	51	64	24	44	54	58

This table reports summary statistics for the term structure of the percentage contributions of distress risk premia, and their components, to the 1-, 3-, 5-, and 10-year bank CDS spreads. We present the results in terms of country averages. Individual bank risk premia are presented in the Internet Appendix. *Total* denotes the risk premia induced by the total default intensity ($\alpha_{i,j} S_t + \gamma_{i,j} C_{t,i} + I_{t,i,j}$); *Systemic* denotes the risk premia induced by the scaled systemic default intensity ($\alpha_i S_t$); *Country* denotes the risk premia induced by the scaled country intensity ($\gamma_{i,j} C_{t,i}$); and *Idiosyncratic* denotes the risk premia induced by the idiosyncratic intensity ($I_{t,i,j}$).

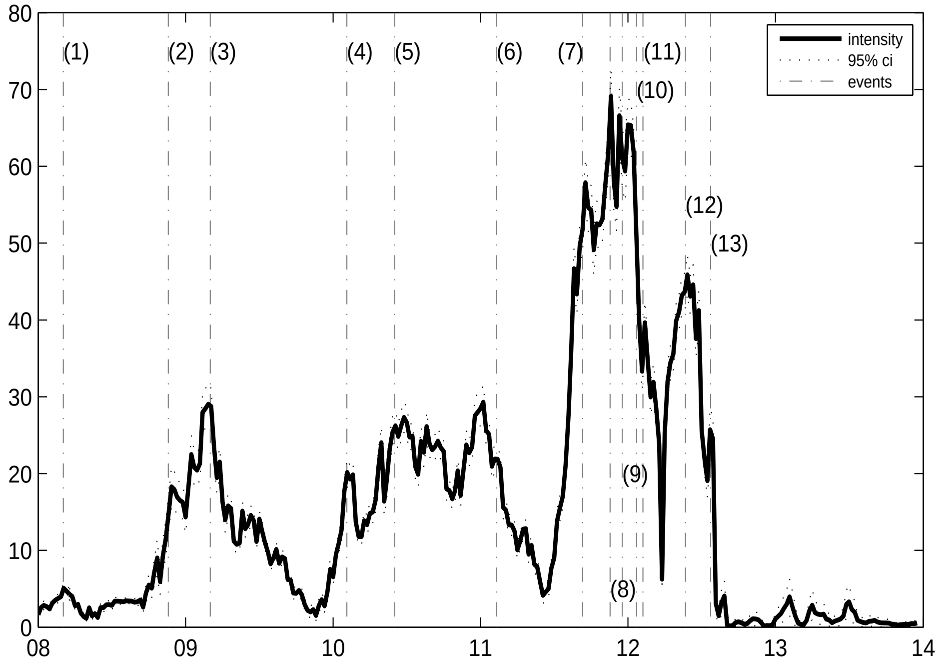

Figure 1: **Europe Systemic Sovereign Credit Risk**

This figure plots the time series of the estimated systemic default intensity (S_t) and its 95% credible interval. The intensity process is measured in basis points. Dotted lines are associated with the following selected events: 1) the Federal Reserve announces the introduction of the TSLF (March 2008); 2) the FED announces the creation of TALF, and a new program for purchasing direct obligations of Fannie Mae and Freddie Mac (November 2008); 3) US authorities announce the launch of the TALF (March 2009); 4) the first austerity package for Greece (February 2010); 5) the European Financial Stability Facility (EFSF) is established (June 2010); 6) Eurozone finance ministers agree to set up the European Stability Mechanism (ESM), which is a permanent bailout fund in the region of 500bn euros that will replace the EFSF (February 2011); 7) Spain passes a constitutional amendment to add in a 'golden rule', such that future budget deficits are kept to a strict limit, and Italy passes a 50bn euro austerity budget to balance the budget by 2013 (September 2011); 8) fears that Europe's sovereign debt crisis is spiralling out of control bring a dramatic increase in debt yields across the eurozone (November 2011); 9) the ECB announces the introduction of the LTRO (December 2011); 10) the 'fiscal pact' agreed by the EU in December 2011 is signed (January 2012); 11) the Greek parliament passes the unpopular austerity bill in parliament (February 2012); 12) Mario Draghi's 'Courageous Leap' speech after the European Union summit in Brussels (May 2012); and 13) Mario Draghi's 'Whatever It Takes' speech at the Global Investment Conference in London (July 2012)

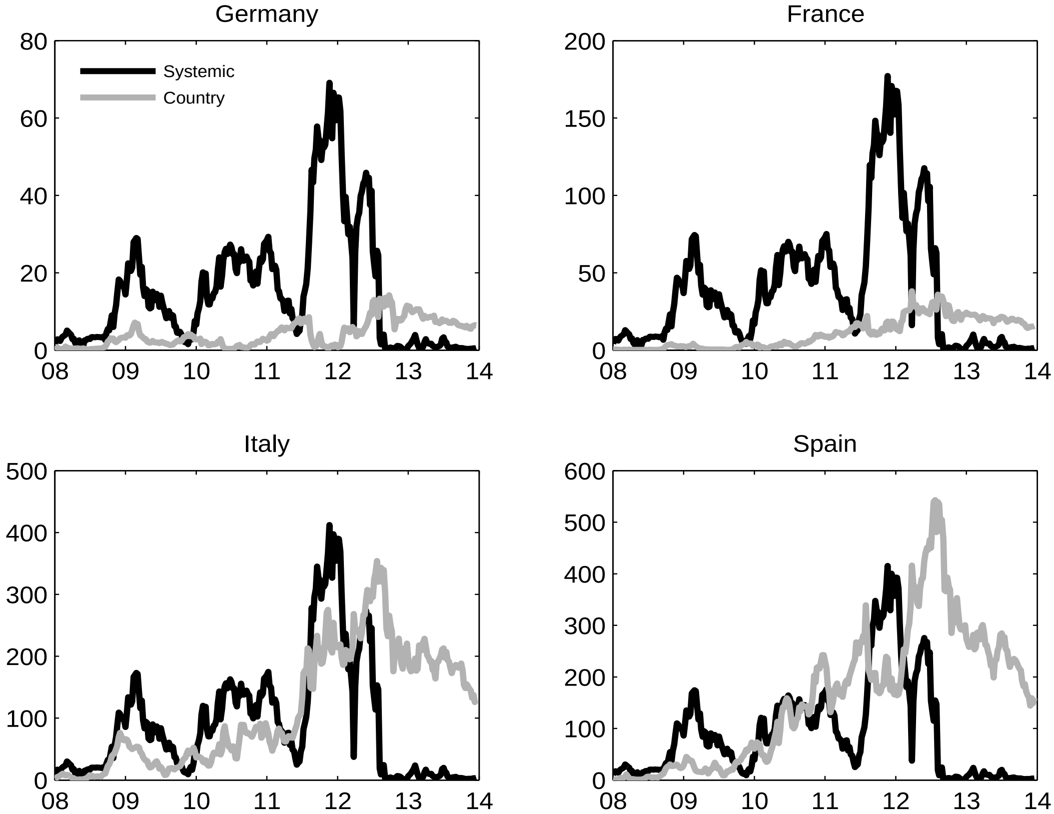

Figure 2: **Systemic and Country Sovereign Credit Risk**

This figure presents the time series of the estimated scaled systemic default ($\alpha_i S_t$) and country ($C_{t,i}$) intensities. The intensity processes is measured in basis points.

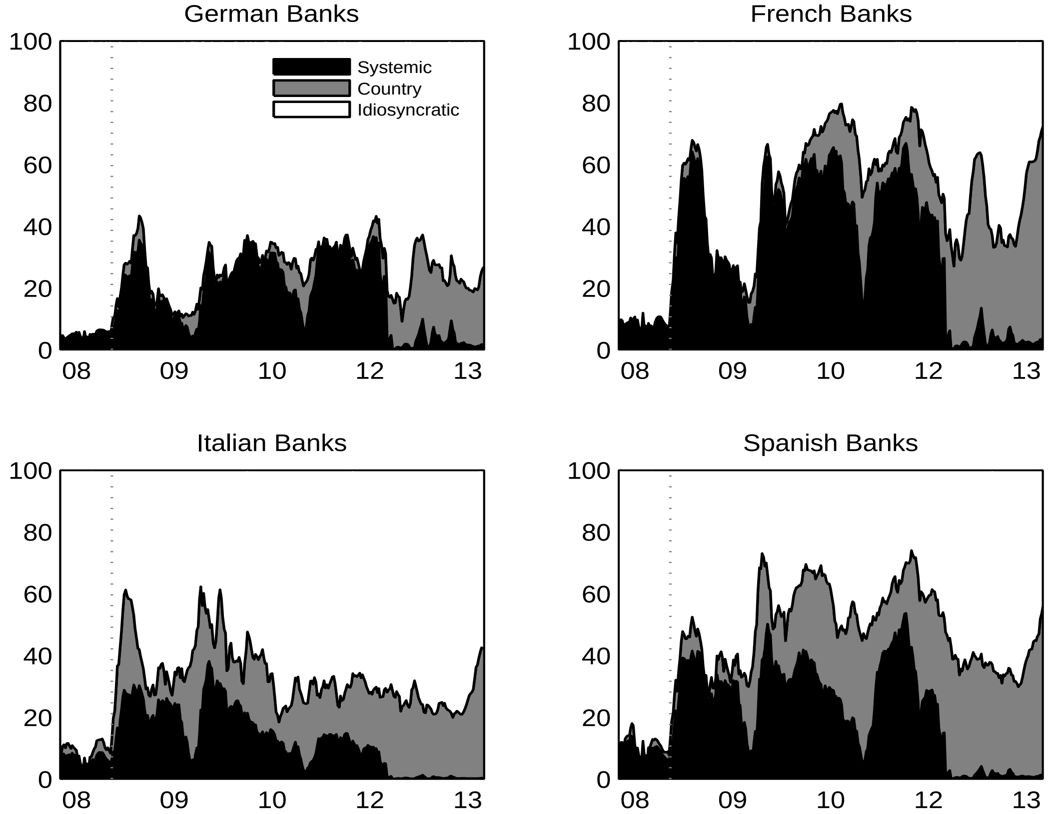

Figure 3: **Bank Systemic, Country and Idiosyncratic Intensity Weights by Country**

This figure presents the average time series of the bank systemic $(\alpha_{i,j}S_t/(\alpha_{i,j}S_t + C_{t,i} + I_{t,i,j}))$, country $(\gamma_{i,j}C_{t,i}/(\alpha_{i,j}S_t + C_{t,i} + I_{t,i,j}))$, and idiosyncratic $(I_{t,i,j}/(\alpha_{i,j}S_t + C_{t,i} + I_{t,i,j}))$ intensity weights by country. The intensity weights are measured in percentage. The dotted line is dated October 2008 when many countries announced comprehensive rescue packages involving some combination of recapitalizations, debt guarantees, and asset purchases.

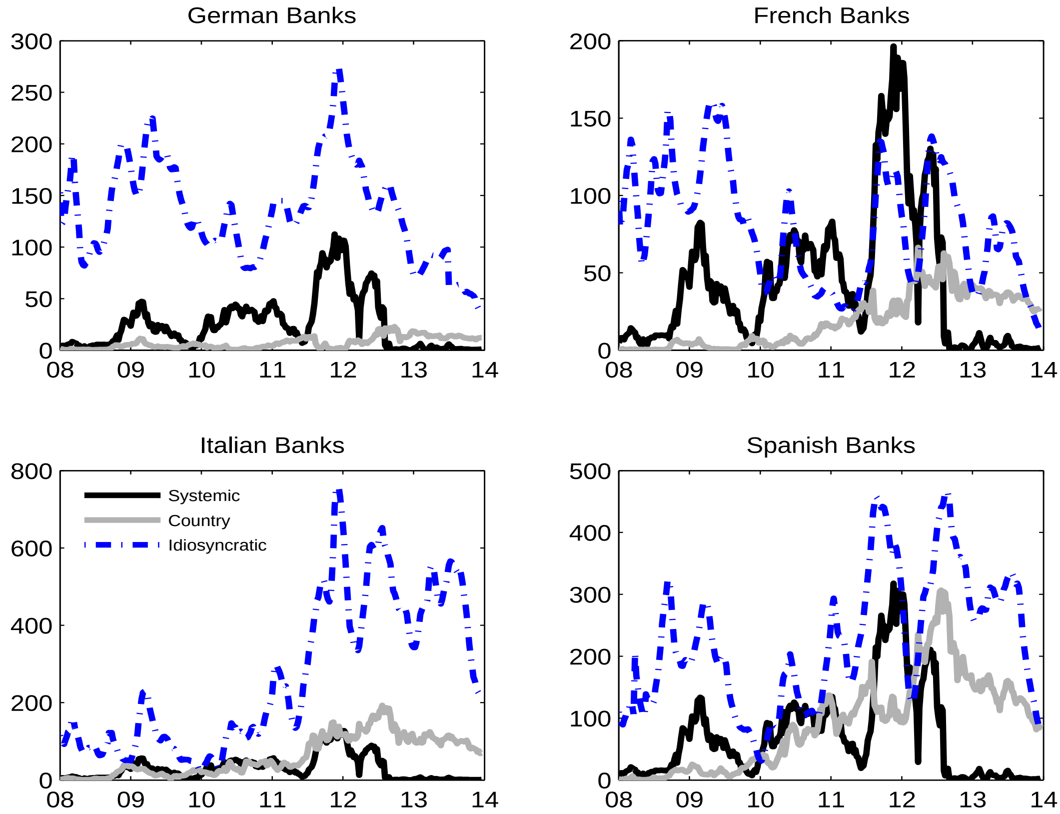

Figure 4: **Average Bank Systemic, Country, and Idiosyncratic Intensities by Country**

This figure presents the country averages of the time series of the estimated bank scaled systemic ($\alpha_{i,j}S_t$), scaled country ($\gamma_{i,j}C_{t,i}$), and idiosyncratic ($I_{t,i,j}$) default intensities. The intensities are measured in basis points.

Internet Appendix

How Much of Bank Credit Risk is Sovereign Risk? Evidence from the Eurozone

by
Junye Li and Gabriele Zinna

I MCMC Algorithm

Bayesian estimation methods are particularly suitable for continuous-time financial models (Johannes and Polson (2009)). They allow us to simultaneously estimate model parameters and latent factors, and to quantify the uncertainty around the estimates. In particular, they are widely used in the estimation of term structure models of interest rates for a number of reasons. First, the likelihood function is generally high dimensional and strongly non-linear in the model parameters, and it is characterized by multiple local maxima. Furthermore, the dynamics of the underlying factors that drive the pricing are generally highly persistent and the estimation sample is relatively small. For this reason, maximum likelihood estimates of term structure models can suffer from small-sample bias (Bauer, Rudebush, and Wu, 2012). In contrast, Bayesian methods do not rely on assumptions on the order of integration in the factors. Therefore, Bayesian methods are probably even more useful in the context of CDS term structure models: CDS prices are non-linear functions of the underlying intensities and the intensities are often non-normally distributed. Despite these well-known difficulties underlying the estimation of CDS term structure models, the MCMC algorithm delivers exact finite sample properties of the estimates. In the following, we describe the MCMC algorithm in detail.

I.1 First-stage Estimation: Sovereign Credit Risk

In the first stage, we estimate a two-factor credit risk model, similar to that found in Ang and Longstaff (2013) and Li and Zinna (2013). The model takes the following state-space form:

Measurement Equations:

$$CDS^{obs}_{t,i} = f(S_t, C_t, \theta^{\mathbb{Q}}, \theta^{\mathbb{Q}}_i, \alpha_i) + \epsilon_{t,i}, , \qquad \epsilon_{t,i} \sim N\left(0, \Sigma_{t,i}\right), \tag{I.1}$$

State Equations:

$$\begin{aligned} S_t &= \eta\tau + (1 - \kappa^{\mathbb{P}}\tau)S_{t-\tau} + \sigma\sqrt{\tau S_{t-\tau}}b_t, & \text{(I.2)}\\ C_{t,i} &= \eta_i\tau + (1 - \kappa^{\mathbb{P}}_i\tau)C_{t-\tau,i} + \sigma_i\sqrt{\tau C_{t-\tau,i}}w_{t,i}, & \text{(I.3)} \end{aligned}$$

As the MCMC algorithm closely follows Li and Zinna (2013), we refer the reader to that paper for a detailed description of the algorithm. The only difference relates to the measurement error variance, which we allow to vary by maturity and over time with the bid-ask spreads, whereas it is constant in Li and Zinna (2013). We specify banks' measurement errors in a similar fashion. A detailed description of how we draw $\Sigma_{t,i}$ is provided in the next section.

I.2 Second-stage Estimation: Bank Credit Risk

The second-stage estimation is carried out bank by bank. For each bank, the measurement equation is given by:

$$CDS^{obs}_{t,i,j} = s\left(S_t, C_{t,i}, I_{t,i,j}, \theta^{\mathbb{Q}}, \theta^{\mathbb{Q}}_i, \theta^{\mathbb{Q}}_{i,j}, \alpha_{i,j}, \gamma_{i,j}\right) + \epsilon_{t,i,j}, \qquad \epsilon_{t,i,j} \sim N\left(0, \Sigma_{t,i,j}\right), \tag{I.4}$$

which uses the first-stage risk-neutral parameter estimates $(\theta^{\mathbb{Q}}, \theta^{\mathbb{Q}}_i)$, as well as the estimated intensities $(S_t, C_{t,i})$ as inputs. We only need to estimate the parameters $(\theta^{\mathbb{Q}}_{i,j})$ together with the sovereign exposures $(\alpha_{i,j}, \gamma_{i,j})$ and the scaling factor $(\sigma^2_{\epsilon,i,j})$, mapping the bid-ask spreads to $\Sigma_{t,i,j}$. The CDS pricing is based on the three-factor pricing function $s(\cdot)$, as descrbed in the Appendix A. The state equation is given by:

$$I_{t,i,j} = \eta_{i,j}\tau + (1-\kappa^{\mathbb{P}}_{i,j}\tau)I_{t-\tau,i,j} + \sigma_{i,j}\sqrt{\tau I_{t-\tau,i,j}}z_{t,i,j}. \tag{I.5}$$

Similar to the first-stage estimation, $\kappa^{\mathbb{P}}_{i,j}$ and $\sigma_{\epsilon,i,j}$ have conjugate priors. However, the remaining parameters and the idiosyncratic bank intensity do not have conjugate priors. For this reason, we use Neal's (2003) slice-sampling method to sample from their posteriors, which can be easily obtained in the same spirit as Li and Zinna (2013). The key difference though is that we draw these parameters conditional on the parameter and state estimates of the first stage.

Draw mean reversion parameter ($\kappa^{\mathbb{P}}_{i,j}$). The parameters $\kappa^{\mathbb{P}}_{i,j}$ only enter the objective dynamics. Therefore, it follows that:

$$\begin{aligned} p(\kappa^{\mathbb{P}}_{i,j}|CDS^{obs}_{1:T,i,j}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-) &\propto p(I_{1:T,i,j}|\kappa^{\mathbb{P}}_{i,j}, \Theta_-)p(\kappa^{\mathbb{P}}_{i,j}) \\ &\propto \exp\left(-\frac{1}{2}\sum_{t=1}^{T}\frac{(I_{t,i,j}-\eta_{i,j}\tau-(1-\kappa^{\mathbb{P}}_{i,j}\tau)I_{t-1,i,j})^2}{\sigma^2_{i,j}\tau I_{t-1,i,j}}\right)p(\kappa^{\mathbb{P}}_{i,j}) \\ &\propto \exp\left(-\frac{1}{2}\sum_{t=1}^{T}\frac{(a_t\kappa^{\mathbb{P}}_{i,j}-b_t)^2}{\sigma^2_{i,j}\tau I_{t-1,i,j}}\right)p(\kappa^{\mathbb{P}}_{i,j}), \end{aligned} \tag{I.6}$$

where $a_t = \tau I_{t-1,i,j}$ and $b_t = \kappa_{i,j}\tau + I_{t-1,i,j}$. Given a flat prior, the posterior distribtion is a normal $\kappa^{\mathbb{P}}_{i,j} \to N(Qm, \mathbb{Q})$, where $m = \sum_{t=1}^{T}\frac{a_t b_t}{\sigma^2_{i,j}\tau I_{t-1,i,j}}$ and $\mathbb{Q}^{-1} = \sum_{t=1}^{T}\frac{a_t^2}{\sigma^2_{i,j}\tau I_{t-1,i,j}}$.

Draw Scaling Factor of Measurement Error Variance ($\sigma^2_{\epsilon,i,j}$). At each time t, we assume normal measurement errors for the observations with variance $\sigma^2_{\epsilon,i,j}BA_t^2$, where $BA_t = |Bid_{t,i,j}(M) - Ask_{t,i,j}(M)|$. Therefore, we have:

$$\begin{aligned} &p(\sigma^2_{\epsilon,i,j}|CDS^{obs}_{1:T,i,j}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-) \\ &\propto p(CDS^{obs}_{1:T,i,j}|\sigma^2_{\epsilon,i,j}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-)p(\sigma^2_{\epsilon,i,j}) \\ &\propto \sigma^{-TM}_{\epsilon,i,j}\exp\left[-\frac{1}{2}\sum_{t=1}^{T}\sigma^{-2}_{\epsilon,i,j}\hat{e}'_{t,i,j}\hat{e}_{t,i,j}\right]p(\sigma^2_{\epsilon,i,j}), \end{aligned} \tag{I.7}$$

where $\hat{e}_{t,i,j}$ is the pricing error $[CDS^{obs}_{t,i,j} - s(\cdot)]BA_t^{-1}$. Thus, $\sigma^{-2}_{\epsilon,i,j}$ has a inverse gamma distribution $IG(a,b)$, where $a = \frac{T}{2}M$ and $b = \sum_{t=1}^{T}\hat{e}'_{t,i,j}\hat{e}_{t,i,j}$, given the flat prior.

Draw Parameters ($\eta_{i,j}$ and $\sigma_{i,j}$). The parameters $\eta_{i,j}$ and $\sigma_{i,j}$ are sampled by the slice-sampling method, as their posterior distributions are not known analytically. Note that they enter into both the pricing formula and the respective objective dynamics. Thus, the joint posterior is:

$$\begin{aligned} &p(\eta_{i,j}, \sigma_{i,j}|CDS^{obs}_{1:T,i,j}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-) \\ &\propto \prod_{t=1}^{T}p(CDS^{obs}_{t,i,j}|S_t, C_{t,i}, I_{t,i,j}, \Theta)p(I_{t,i,j}|I_{t-1,i,j}, \eta_{i,j}, \sigma_{i,j})p(\eta_{i,j}, \sigma_{i,j}) \\ &\propto \frac{1}{\sigma^T_{i,j}}\exp\left[-\frac{1}{2}\sum_{t=1}^{T}\left(\sigma^{-2}_{\epsilon,i,j}\hat{e}'_{t,i,j}\hat{e}_{t,i,j} + \frac{A_t}{\sigma^2_{i,j}\tau I_{t-1,i,j}}\right)\right]p(\eta_{i,j}, \sigma_{i,j}), \end{aligned} \tag{I.8}$$

where $A_t = (I_{t,i,j} - \eta_{i,j}\tau - (1-\kappa^{\mathbb{P}}_{i,j}\tau)I_{t-1,i,j})^2$.

Draw Risk-neutral Parameters ($\kappa^{\mathbb{Q}}_{i,j}$ and $\gamma_{i,j}$). The parameters $\kappa^{\mathbb{Q}}_{i,j}$ and $\gamma_{i,j}$ are sampled by the slice-sampling method, as their conditional distributions are not known analytically. Note that the parameters $\kappa^{\mathbb{Q}}_{i,j}$ and $\gamma_{i,j}$ only enter into the pricing formula $s(\cdot)$. Therefore, the joint posterior is:

$$\begin{aligned} & p(\kappa^{\mathbb{Q}}_{i,j}, \gamma_{i,j} | CDS^{obs}_{1:T,i,j}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_{-}) \\ & \propto \prod_{t=1}^{T} p(CDS^{obs}_{t,i,j} | S_t, C_{t,i}, I_{t,i,j}, \Theta) p(\kappa^{\mathbb{Q}}_{i,j}, \gamma_{i,j}) \\ & \propto \exp\left[-\frac{1}{2} \sum_{t=1}^{T} \sigma^{-2}_{\epsilon,i,j} \hat{e}'_{t,i,j} \hat{e}_{t,i,j} \right] p(\kappa^{\mathbb{Q}}_{i,j}, \gamma_{i,j}). \end{aligned} \tag{I.9}$$

Draw Bank-specific Intensity ($I_{t,i,j}$). The latent state $I_{t,i,j}$ is sampled individually by the slice-sampling method. For $t = 1, \ldots, T$, the conditional posterior is:

$$\begin{aligned} & p(I_{t,i,j} | CDS^{obs}_{1:T,i,j}, S_{1:T}, C_{1:T,i}, I_{-t,i,j} \Theta) \\ & \propto p(CDS^{obs}_{t,i,j} | S_t, C_{t,i}, I_{t,i,j}, \Theta) p(I_{t,i,j} | I_{t+1,i,j}, I_{t-1,i,j}, \Theta) \\ & \propto p(CDS^{obs}_{t,i,j} | S_t, C_{t,i}, I_{t,i,j}, \Theta) p(I_{t+1,i,j} | I_{t,i,j}, \Theta) p(I_{t,i,j} | I_{t-1,i,j}, \Theta), \end{aligned} \tag{I.10}$$

where the first term in (I.10) is:

$$p(CDS^{obs}_{t,i,j} | \cdot) \quad \propto \quad \exp\left[-\frac{1}{2} \sigma^{-2}_{\epsilon,i,j} \hat{e}'_{t,i,j} \hat{e}_{t,i,j} \right], \tag{I.11}$$

and the second and third terms are given by:

$$p(I_{t+1,i,j} | \cdot) \quad \propto \quad \frac{1}{\sigma_{i,j} \sqrt{\tau I_{t,i,j}}} \exp\left(-\frac{1}{2} \frac{(I_{t+1,i,j} - \eta_{i,j}\tau - (1 - \kappa^{\mathbb{P}}_{i,j}\tau) I_{t,i,j})^2}{\sigma^2_{i,j} \tau I_{t,i,j}} \right), \tag{I.12}$$

$$p(I_{t,i,j} | \cdot) \quad \propto \quad \exp\left(-\frac{1}{2} \frac{(I_{t,i,j} - \eta_{i,j}\tau - (1 - \kappa^{\mathbb{P}}_{i,j}\tau) I_{t-1,i,j})^2}{\sigma^2_{i,j} \tau I_{t-1,i,j}} \right). \tag{I.13}$$

At time $t = T$, the posterior simplifies to:

$$p(I_{T,i,j} | \cdot) \propto p(CDS^{obs}_{T,i,j} | S_T, C_{T,i}, I_{T,i,j}, \Theta) p(I_{T,i,j} | I_{T-1,i,j}, \Theta), \tag{I.14}$$

and at time $t = 1$ it becomes:

$$p(I_{1,i,j} | \cdot) \propto p(CDS^{obs}_{1,i,j} | S_1, C_{1,i}, I_{1,i,j}, \Theta) p(I_{2,i,j} | I_{1,i,j}, \Theta). \tag{I.15}$$

II Additional Tables

Table A1: **Mid Price and Bid-Ask Spread Average Term Structures**

	CDS					BID-ASK				
ID	1yr	3yr	5yr	7yr	10yr	1yr	3yr	5yr	7yr	10yr
GER	17	28	43	52	59	3	3	3	4	5
DB	83	116	145	154	160	15	12	7	9	9
CB	67	91	112	117	122	16	14	11	10	10
DZ	99	118	132	135	138	23	17	14	12	12
LBW	92	111	129	132	135	23	17	14	13	12
BYLAN	103	121	135	140	144	20	15	11	11	11
NDB	176	193	206	208	210	20	15	11	11	11
HSH	66	97	122	132	138	11	10	7	8	9
FRA	35	57	80	92	100	5	4	4	5	6
BNP	66	97	122	132	138	11	10	7	8	9
CA	87	123	152	163	169	14	12	7	10	10
SG	95	129	158	168	175	15	12	8	10	10
NTX	134	164	185	191	195	34	23	18	16	15
ITA	142	190	213	219	220	14	9	6	7	9
ISP	139	176	199	208	214	19	14	9	11	11
UI	164	203	226	234	239	22	15	9	13	13
MPS	259	287	303	306	309	30	19	13	16	16
BP	274	308	329	335	337	42	27	18	20	20
UBI	166	195	218	223	228	33	22	17	16	15
ESP	155	202	221	226	225	14	9	6	8	9
BST	135	175	201	208	214	18	13	8	11	10
BBVA	142	184	211	219	224	19	13	8	10	9
BCXA	181	217	232	234	235	48	33	24	22	19
BPE	338	379	401	402	401	63	40	29	28	26
BSB	328	360	382	381	380	63	38	28	27	25

This table report average CDS spread term structures, and average bid-ask spread term structures, for the German, French, Italian, and Spanish sovereigns and the indicated banks. The sample consists of weekly observations from January 9, 2008, to December 18, 2013. Source: CMA.

Table A2: **Pricing Errors**

	Panel A: MAPE					Panel B: MAPPE				
	1yr	3yr	5yr	7yr	10yr	1yr	3yr	5yr	7yr	10yr
GER	5.4	5.6	3.9	3.5	4.1	38.6	21.3	9.6	6.8	7.2
DB	15.5	10.3	9.8	12.9	15.5	34.7	10.7	8.3	10.6	11.8
CB	24.9	14.6	12.6	13.4	15.0	48.4	13.1	9.7	10.1	11.1
DZ	16.1	10.7	8.0	10.0	8.8	23.7	11.2	7.2	8.4	7.1
LBW	21.6	14.4	11.8	13.2	11.5	22.4	12.3	9.6	10.6	8.7
BYLAN	20.3	11.1	9.3	11.3	12.9	23.0	10.1	7.7	9.6	10.2
NDB	15.3	12.0	9.2	9.2	8.7	20.2	10.7	7.5	6.7	6.5
HSH	22.3	12.5	10.2	12.2	13.3	13.2	6.1	4.8	6.0	6.6
FRA	5.2	3.6	3.4	4.6	5.6	24.2	8.1	5.0	4.9	5.9
BNP	16.4	10.1	8.1	12.5	11.7	35.1	9.5	7.5	10.0	9.6
CA	21.5	11.4	9.7	12.7	15.4	34.5	8.9	7.1	8.5	9.9
SG	21.6	10.9	9.5	12.3	14.7	34.9	8.9	6.4	7.8	8.6
NTX	30.3	17.5	12.0	14.8	13.4	25.5	10.6	6.7	7.7	7.9
ITA	25.4	10.5	4.8	6.9	8.6	20.7	6.0	3.4	2.9	4.7
ISP	26.8	13.3	9.5	11.6	14.1	24.1	7.8	6.4	6.8	9.4
UI	25.9	13.0	9.8	12.5	14.9	20.0	6.3	5.4	5.8	7.5
MPS	39.8	21.6	13.2	14.5	16.1	19.2	8.3	5.7	6.0	7.5
BP	37.2	18.6	13.1	14.5	16.8	16.1	6.2	4.4	4.7	5.6
UBI	31.2	18.6	17.2	15.1	18.1	25.4	10.9	8.0	6.5	9.1
ESP	21.1	11.7	4.5	5.6	10.1	18.6	6.6	2.9	2.8	4.9
BST	29.0	12.8	10.9	10.9	14.5	29.0	7.6	5.9	5.5	7.2
BBVA	28.2	12.8	10.5	10.5	13.0	28.2	7.2	5.6	5.2	6.7
BCXA	29.2	15.3	13.6	13.4	16.5	18.9	8.0	6.3	6.2	8.0
BPE	44.3	22.4	16.4	17.5	23.6	17.3	6.4	4.6	4.8	6.1
BSB	43.6	20.5	16.3	17.1	24.4	18.2	6.1	4.7	4.8	6.5

This table reports the mean absolute pricing errors (MAPE) in the the left panel, and the mean absolute percentage pricing errors (MAPPE) in the right panel, for the CDS with the indicated maturities. The results are grouped by country. The estimation is performed with the Bayesian algorithm described in Section 4, based on weekly data from January 9, 2008, to December 18, 2013.

Table A3: **Individual Bank Parameter Estimates**

	$\eta_{i,j}$	$\kappa^{\mathbb{P}}_{i,j}$	$\sigma_{i,j}$	$k^{\mathbb{Q}}_{i,j}$	$\alpha_{i,j}$	$\gamma_{i,j}$	$\sigma^{i,j}_{\epsilon}$
Panel A: German Banks (i=GER)							
DB	0.34	0.94	0.15	0.14	1.2	1.83	5.56
	[0.29;0.39]	[0.33;1.52]	[0.13;0.17]	[0.10;0.18]	[1.02;1.37]	[1.69;1.96]	[3.58;7.04]
CB	0.05	0.42	0.09	-0.13	2.32	2.38	6.76
	[0.03;0.08]	[0.12;0.70]	[0.08;0.10]	[-0.15;-0.10]	[2.05;2.60]	[2.09;2.66]	[5.47;7.88]
DZ	0.06	0.35	0.08	-0.02	1.42	1.77	5.32
	[0.03;0.10]	[0.11;0.59]	[0.07;0.09]	[-0.04;0.00]	[1.24;1.60]	[1.40;2.14]	[3.35;6.95]
LBW	0.02	0.34	0.09	-0.09	2.47	1.96	6.32
	[0.01;0.04]	[0.10;0.57]	[0.08;0.10]	[-0.10;-0.07]	[2.05;2.91]	[1.14;2.76]	[4.70;7.79]
BYLAN	0.31	0.6	0.12	0.17	1.57	1.42	3.08
	[0.25;0.37]	[0.23;0.97]	[0.11;0.14]	[0.13;0.21]	[1.29;1.85]	[1.17;1.66]	[1.75;4.18]
NDB	0.14	0.22	0.08	0	1.18	0.03	4.48
	[0.09;0.20]	[0.06;0.38]	[0.07;0.09]	[-0.02;0.03]	[0.94;1.41]	[0.01;0.04]	[2.39;6.48]
HSH	0.77	0.42	0.17	0.22	1.24	1.85	5.71
	[0.67;0.88]	[0.12;0.72]	[0.15;0.19]	[0.18;0.26]	[0.86;1.63]	[1.23;2.49]	[2.69;8.82]
Panel B: French Banks (i=FRA)							
	$\eta_{i,j}$	$\kappa^{\mathbb{P}}_{i,j}$	$\sigma_{i,j}$	$k^{\mathbb{Q}}_{i,j}$	$\alpha_{i,j}$	$\gamma_{i,j}$	$\sigma^{i,j}_{\epsilon}$
BNP	0.05	0.7	0.11	-0.05	2.37	1.57	3.77
	[0.03;0.08]	[0.21;1.19]	[0.09;0.12]	[-0.10;0.00]	[2.12;2.63]	[1.50;1.64]	[3.05;4.40]
CA	0.18	0.83	0.14	0.02	2.7	1.99	4.73
	[0.15;0.21]	[0.27;1.38]	[0.12;0.15]	[-0.02;0.06]	[2.42;2.99]	[1.89;2.09]	[3.43;5.81]
SG	0.18	0.68	0.13	0.02	3.08	1.91	4.46
	[0.15;0.20]	[0.21;1.13]	[0.12;0.15]	[-0.02;0.05]	[2.83;3.33]	[1.81;2.00]	[3.04;5.59]
NTX	0.04	0.36	0.11	-0.06	3.23	1.51	3.64
	[0.02;0.07]	[0.10;0.62]	[0.10;0.12]	[-0.08;-0.04]	[2.94;3.52]	[1.35;1.67]	[2.64;4.52]
Panel C: Italian Banks (i=ITA)							
	$\eta_{i,j}$	$\kappa^{\mathbb{P}}_{i,j}$	$\sigma_{i,j}$	$k^{\mathbb{Q}}_{i,j}$	$\alpha_{i,j}$	$\gamma_{i,j}$	$\sigma^{i,j}_{\epsilon}$
ISP	0	0.49	0.19	0.02	0	0.77	3.6
	[0.00;0.01]	[0.12;0.86]	[0.17;0.20]	[0.00;0.04]	[0.00;0.00]	[0.75;0.80]	[2.23;4.78]
UI	0.07	0.52	0.21	0.08	0	0.91	3.71
	[0.04;0.09]	[0.14;0.88]	[0.19;0.22]	[0.05;0.10]	[0.00;0.00]	[0.88;0.94]	[2.09;5.18]
MPS	0.01	0.22	0.16	-0.04	3.41	0.48	4.26
	[0.00;0.02]	[0.04;0.40]	[0.15;0.17]	[-0.06;-0.02]	[3.17;3.66]	[0.45;0.52]	[2.67;5.83]
BP	0.04	0.25	0.16	-0.02	3.36	0.51	3.72
	[0.01;0.06]	[0.06;0.44]	[0.15;0.18]	[-0.04;-0.00]	[2.88;3.85]	[0.45;0.57]	[2.05;5.28]
UBI	0.15	0.23	0.12	-0.08	2.98	0.04	5.17
	[0.12;0.17]	[0.06;0.40]	[0.11;0.13]	[-0.10;-0.06]	[2.59;3.37]	[0.02;0.06]	[3.52;6.71]

Panel D: Spanish Banks (i=SPA)							
	$\eta_{i,j}$	$\kappa^{\mathbb{P}}_{i,j}$	$\sigma_{i,j}$	$k^{\mathbb{Q}}_{i,j}$	$\alpha_{i,j}$	$\gamma_{i,j}$	$\sigma^{i,j}_{\epsilon}$
BST	0.01	0.52	0.12	-0.09	3.98	0.54	3.98
	[0.00;0.01]	[0.15;0.89]	[0.11;0.13]	[-0.11;-0.07]	[3.77;4.19]	[0.52;0.56]	[3.11;4.72]
BBVA	0.01	0.58	0.12	-0.1	4.31	0.64	3.96
	[0.00;0.01]	[0.16;1.00]	[0.11;0.13]	[-0.12;-0.08]	[4.10;4.52]	[0.62;0.67]	[3.12;4.64]
BCXA	0.27	0.41	0.17	0.01	2.42	0.11	3.93
	[0.21;0.34]	[0.12;0.70]	[0.15;0.18]	[-0.02;0.03]	[1.98;2.85]	[0.09;0.13]	[2.15;5.52]
BPE	0.07	0.32	0.17	-0.07	5.96	0.74	3.64
	[0.03;0.12]	[0.08;0.56]	[0.16;0.19]	[-0.10;-0.04]	[4.77;7.15]	[0.63;0.86]	[2.39;4.77]
BSB	0.26	0.44	0.2	-0.01	6.32	0.79	3.36
	[0.19;0.33]	[0.12;0.75]	[0.18;0.22]	[-0.04;0.02]	[5.29;7.35]	[0.70;0.88]	[2.00;4.52]

This table reports posterior means and 95% credible intervals (in squared brackets) of the parameter estimates resulting from the second-stage estimation on bank CDSs. The results are grouped by country. The estimation is performed with the Bayesian algorithm described in Section 4, based on weekly data from January 9, 2008, to December 18, 2013.

Table A4: **Principal Component Analysis of Bank-idiosyncratic Intensities**

	PCs All Banks				PCs by Country		
	PC1	PC2	PC3		PC1	PC2	PC3
DB	0.08	-0.01	0.05	DB	0.21	0.58	-0.72
CB	0.05	-0.02	0.02	CB	0.08	0.28	-0.14
DZ	0.01	-0.01	0.03	DZ	0.09	0.12	-0.04
LBW	0.03	-0.01	0.01	LBW	0.09	0.21	0.18
BYLAN	0.11	0.01	0.01	BYLAN	0.27	0.60	0.65
NDB	0.02	0.00	0.07	NDB	0.11	0.17	0.11
HSH	0.11	0.09	0.63	HSH	0.92	-0.39	-0.04
BNP	0.07	0.01	-0.02	$cR^2(\%)$	66.1	86.0	92.0
CA	0.06	0.00	-0.03				
SG	0.09	0.00	-0.08	BNP	0.38	0.17	0.03
NTX	0.04	-0.05	0.09	CA	0.56	0.17	-0.77
ISP	0.37	0.41	-0.21	SG	0.59	0.39	0.62
UI	0.48	0.52	-0.22	NTX	0.43	-0.89	0.13
MPS	0.25	-0.08	0.23	$cR^2(\%)$	67.2	89.5	96.9
BP	0.42	0.03	0.50				
UBI	0.16	-0.07	0.09	ISP	0.47	-0.39	-0.16
BST	0.06	0.01	0.01	UI	0.60	-0.49	-0.06
BBVA	0.05	0.00	0.00	MPS	0.35	0.59	-0.72
BCXA	0.14	-0.36	0.19	BP	0.52	0.48	0.65
BPE	0.36	-0.44	-0.22	UBI	0.17	0.17	0.17
BSB	0.40	-0.46	-0.29	$cR^2(\%)$	72.9	90.2	96.7
$cR^2(\%)$	53.9	68.8	77.4				
				BST	0.08	0.04	-0.70
				BBVA	0.07	0.08	-0.66
				BCXA	0.29	0.95	0.10
				BPE	0.63	-0.17	0.24
				BSB	0.71	-0.25	-0.11
				$cR^2(\%)$	78.2	92.7	96.7

This table reports the principal component analysis of the changes in bank-idiosyncratic default intensities. The principal component analysis is displayed for all European countries included in our sample, in the left panel, and for country groups, in the right panel.

Table A5: **Term Structure of Individual Bank Risk Premia Components: Germany**

	Total Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
DB	68	5	56	76	78	5	66	85	83	4	74	89
CB	70	6	57	86	82	4	71	92	89	2	84	94
DZ	62	10	44	79	75	9	58	88	84	5	74	92
LBW	66	8	50	81	78	6	65	89	87	4	80	93
BYLAN	56	7	41	72	67	7	51	81	75	6	61	85
NDB	37	7	27	50	48	8	38	63	62	5	52	73
HSH	34	7	22	48	45	8	29	60	51	8	36	66
	Systemic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
DB	17	14	0	47	19	15	0	55	18	15	0	55
CB	26	20	0	59	25	20	0	60	18	15	0	46
DZ	20	18	0	67	22	20	0	73	20	18	0	69
LBW	23	17	0	59	23	17	0	59	18	14	0	51
BYLAN	17	13	0	45	20	15	0	48	18	14	0	47
NDB	14	10	0	33	18	13	0	41	17	12	0	42
HSH	10	9	0	31	13	11	0	38	13	11	0	40
	Country Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
DB	16	13	1	55	22	17	1	64	25	16	3	61
CB	14	10	1	43	21	13	1	55	21	12	2	51
DZ	17	17	1	57	24	21	2	70	28	21	4	71
LBW	17	18	1	59	24	22	1	72	27	22	2	73
BYLAN	12	13	0	46	19	17	1	58	25	18	2	62
NDB	0	0	0	0	0	0	0	1	4	3	0	12
HSH	7	6	1	25	11	10	1	37	15	11	2	42
	Idiosyncratic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
DB	35	9	18	55	36	11	19	60	40	11	24	64
CB	30	10	6	51	35	12	8	62	49	12	16	76
DZ	24	9	9	39	28	12	10	50	35	15	14	63
LBW	26	8	9	43	31	11	10	55	42	14	17	70
BYLAN	26	6	12	39	28	8	13	47	32	9	17	52
NDB	22	3	17	27	30	5	21	37	40	6	29	49
HSH	17	3	12	21	20	4	13	26	24	4	16	31

This table reports summary statistics for the term structure of the percentage contributions of distress risk premia and their components, to the 1-, 3-, 5-, and 10-year bank CDS spreads for the indicated German banks. *Total* denotes the risk premia induced by the total default intensity ($\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j}$); *Systemic* denotes the risk premia induced by the scaled systemic default intensity ($\alpha_{i,j}S_t$); *Country* denotes the risk premia induced by the scaled country intensity ($\gamma_{i,j}C_{t,i}$); and *Idiosyncratic* denotes the risk premia induced by the idiosyncratic intensity ($I_{t,i,j}$).

Table A6: **Term Structure of Individual Bank Risk Premia Components: France**

	Total Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BNP	79	6	65	87	88	5	77	93	93	3	87	97
CA	77	6	63	85	85	5	73	91	89	3	82	94
SG	74	7	57	83	83	6	68	89	87	4	79	93
BFCM	39	1	39	44	54	1	53	59	76	2	73	85
NTX	65	11	49	85	77	9	63	92	86	5	78	96
	Systemic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BNP	31	22	0	69	29	21	0	67	21	16	0	50
CA	26	20	0	62	25	19	0	59	18	14	0	48
SG	28	20	0	61	25	19	0	58	18	14	0	42
BFCM	1	2	0	8	2	3	0	13	5	7	0	32
NTX	23	19	0	69	21	18	0	65	15	14	0	53
	Country Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BNP	27	23	2	72	36	26	5	83	45	23	13	84
CA	25	21	2	70	33	24	4	79	38	21	10	76
SG	23	20	2	66	32	23	5	75	37	21	11	73
BFCM	0	0	0	2	1	1	0	5	8	7	1	35
NTX	17	16	1	65	26	22	1	79	34	23	4	84
	Idiosyncratic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BNP	21	14	4	54	21	16	5	61	26	16	8	65
CA	26	16	9	62	33	15	13	66	33	15	13	66
SG	25	13	10	56	32	14	16	62	32	14	16	62
BFCM	52	3	42	53	62	9	32	71	62	9	32	71
NTX	29	15	4	55	37	19	6	68	37	19	6	68

This table reports summary statistics for the term structure of the percentage contributions of distress risk premia, and their components, to the 1-, 3-, 5-, and 10-year bank CDS spreads for the indicated French banks. *Total* denotes the risk premia induced by the total default intensity ($\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j}$); *Systemic* denotes the risk premia induced by the scaled systemic default intensity ($\alpha_{i,j}S_t$); *Country* denotes the risk premia induced by the scaled country intensity ($\gamma_{i,j}C_{t,i}$); and *Idiosyncratic* denotes the risk premia induced by the idiosyncratic intensity ($I_{t,i,j}$).

Table A7: **Term Structure of Individual Bank Risk Premia Components: Italy**

	Total Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
ISP	61	5	50	72	75	5	64	85	87	3	79	92
UI	59	6	47	72	72	6	60	84	84	4	75	90
MPS	50	7	38	69	65	7	53	81	79	4	71	90
BP	50	9	37	75	63	8	49	82	77	5	67	89
UBI	50	9	38	71	60	7	49	75	72	3	63	78
	Systemic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
ISP	0	0	0	0	0	0	0	1	1	1	0	2
UI	0	0	0	0	0	0	0	1	1	1	0	2
MPS	0	0	0	0	0	0	0	0	1	1	0	2
BP	16	13	0	55	16	13	0	53	11	8	0	34
UBI	22	16	0	59	22	16	0	57	14	10	0	36
	Country Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
ISP	38	14	9	70	53	15	19	82	70	10	42	91
UI	36	15	8	70	50	16	18	81	65	12	40	87
MPS	31	12	8	65	43	14	18	78	56	12	33	86
BP	14	6	3	29	22	8	7	42	39	9	21	62
UBI	2	1	1	5	3	1	1	7	11	3	5	20
	Idiosyncratic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
ISP	22	9	2	40	21	10	2	44	16	7	1	36
UI	22	9	2	39	22	10	2	42	18	8	3	35
MPS	19	6	3	29	21	7	3	34	21	8	3	36
BP	20	6	6	30	24	7	7	38	25	7	7	40
UBI	26	7	10	35	34	8	15	47	46	7	30	56

This table reports summary statistics for the term structure of the percentage contributions of distress risk premia, and their components, to the 1-, 3-, 5-, and 10-year bank CDS spreads for the indicated Italian banks. *Total* denotes the risk premia induced by the total default intensity ($\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j}$); *Systemic* denotes the risk premia induced by the scaled systemic default intensity ($\alpha_{i,j}S_t$); *Country* denotes the risk premia induced by the scaled country intensity ($\gamma_{i,j}C_{t,i}$); and *Idiosyncratic* denotes the risk premia induced by the idiosyncratic intensity ($I_{t,i,j}$).

Table A8: **Term Structure of Individual Bank Risk Premia Components: Spain**

	Total Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BST	69	6	60	79	80	4	73	86	89	2	85	91
BBVA	70	6	63	80	81	3	74	87	89	1	85	91
BANKIA	37	7	27	54	46	7	34	61	56	6	43	67
BCXA	51	8	42	76	62	7	52	82	73	5	64	85
BPE	57	5	45	68	68	4	58	76	79	3	72	84
BSB	58	5	46	69	68	4	57	76	77	4	68	83
	Systemic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BST	27	19	0	58	25	18	0	57	16	12	0	42
BBVA	27	19	0	61	24	18	0	58	15	12	0	43
BANKIA	11	9	0	33	11	9	0	33	8	7	0	27
BCXA	15	14	0	63	16	15	0	64	12	11	0	49
BPE	17	12	0	42	15	11	0	38	10	8	0	26
BSB	17	12	0	45	15	11	0	39	10	8	0	28
	Country Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BST	24	13	3	49	34	15	7	63	51	15	20	76
BBVA	26	14	5	56	36	16	9	70	53	15	22	81
BANKIA	6	4	1	15	9	6	1	23	18	9	4	38
BCXA	5	3	0	17	8	5	1	25	18	9	3	44
BPE	16	8	2	32	24	11	4	43	36	12	12	56
BSB	18	11	2	42	26	14	5	53	37	15	12	60
	Idiosyncratic Risk Premia											
	3-year				5-year				10-year			
	Mean	SDev	Min	Max	Mean	SDev	Min	Max	Mean	SDev	Min	Max
BST	18	13	2	50	21	14	2	59	22	14	3	60
BBVA	17	13	2	51	19	14	3	58	20	14	4	57
BANKIA	21	4	13	26	26	5	15	33	29	6	18	39
BCXA	31	7	8	40	37	9	10	51	42	9	16	60
BPE	23	6	12	39	28	8	14	49	32	9	17	56
BSB	23	8	9	41	27	10	12	50	30	10	15	54

This table reports summary statistics for the term structure of the percentage contributions of distress risk premia, and their components, to the 1-, 3-, 5-, and 10-year bank CDS spreads for the indicated Spanish banks. *Total* denotes the risk premia induced by the total default intensity ($\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j}$); *Systemic* denotes the risk premia induced by the scaled systemic default intensity ($\alpha_{i,j}S_t$); *Country* denotes the risk premia induced by the scaled country intensity ($\gamma_{i,j}C_{t,i}$); and *Idiosyncratic* denotes the risk premia induced by the idiosyncratic intensity ($I_{t,i,j}$).

III Additional Figures

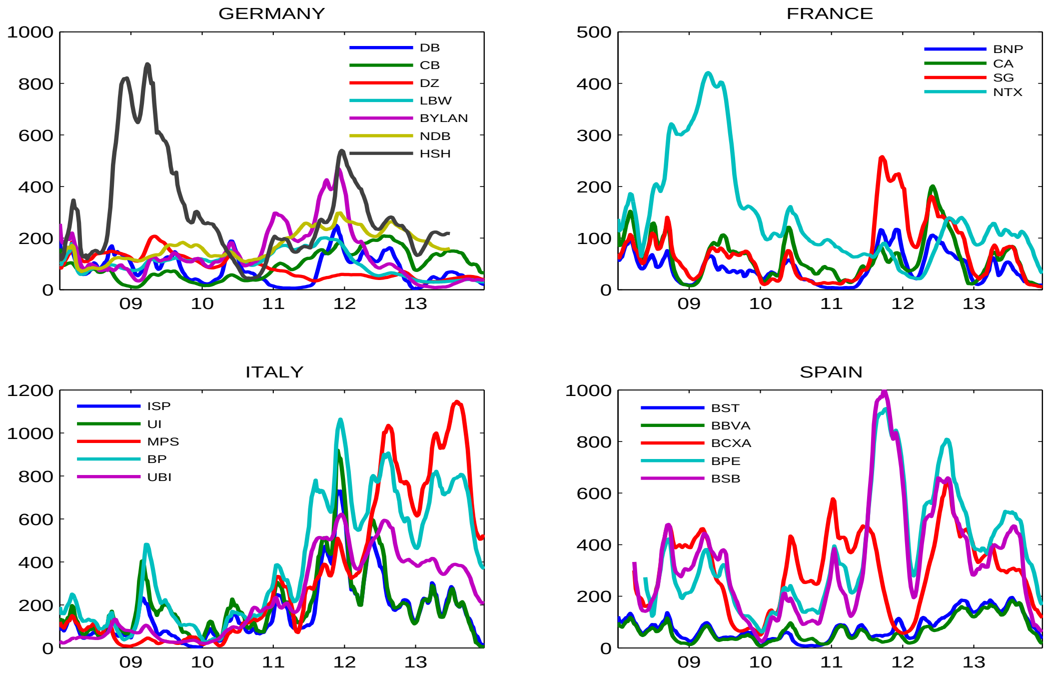

Figure A.1: **Idiosyncratic Intensities by Country**

This figure presents the estimated idiosyncratic bank intensities. The intensities are measured in basis points.

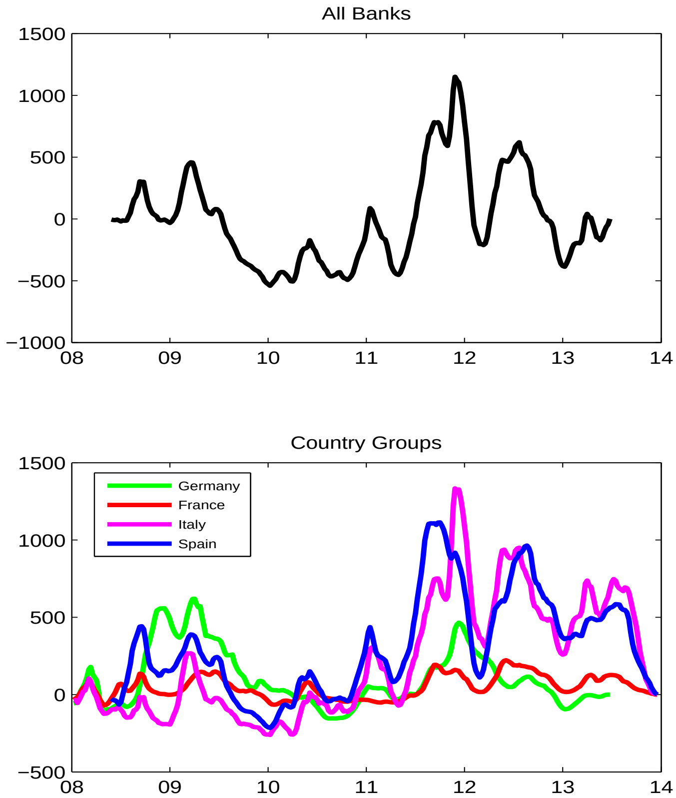

Figure A.2: **Principal Component Analysis of Bank Idiosyncratic Intensities**

The *All Banks* panel presents the first principal component of the bank idiosyncratic intensities. The *Country Groups* panel repeats the principal component analysis for each country separately. (Note that we perform the PC analysis on the intensities in first differences and we plot the cumulative sum)