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

Junye Li† Gabriele Zinna‡

November 2015

Abstract

We uncover novel evidence on large Eurozone banks' exposures to sovereign credit risk by estimating a multivariate credit risk model on CDS data of different maturities. About one third of short-term banks' credit risk is due to sovereign risk, either originating from their exposures to joint sovereign defaults, or to the default risk specific to the domestic sovereign. When the effect of credit risk premia is taken into account, sovereign risk can explain up to 60% of banks' longer-term CDSs. Moreover, market-based measures of bank sovereign exposures partly relate to bank size, holdings of government bonds, and expected government support.

Keywords: Bank credit risk; sovereign exposures; systemic risk; credit default swaps; distress risk premia.

JEL Classification: F34; G12; G15.

*The authors are indebted to Piergiorgio Alessandri, Marianna Caccavaio, Nicola Cetorelli, Ricardo Correa, Nicola Gennaioli, Giuseppe Grande, Taneli Makinen, David Lando, George Pennacchi, Marcello Pericoli, Marco Taboga, and Kenneth Singleton for their constructive comments. We are also grateful for comments received from seminar participants at the Bank of Italy, the Bank of England, ESSEC Business School, the Sveriges Riksbank, the European Banking Authority (3rd Policy Research Workshop on "How to measure the riskiness of banks"), and the Banco Central do Brasil (X Annual Seminar on Risk, Financial Stability, and Banking). 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.

†ESSEC Business School, Paris-Singapore. Email: li@essec.edu

‡Bank of Italy, Rome. Email: Gabriele.Zinna@bancaditalia.it.

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 (Gennaioli, Martin and Rossi, 2013; Acharya, Dreschsler and Schnabl, 2013; Acharya and Rajan, 2013; Korte and Steffen, 2014). In this regard, the Euro area is of particular interest and serves a natural laboratory to assess the bank-sovereign nexus. In a number of countries, sovereign public finances were clearly the initial source of fragility, which then transmitted to the banks. In some other countries, the sovereigns came under strain as a result of undertaking many policy measures to respond to turmoils in the financial sector and this sovereign fragility then eventually fed back to the banks (Acharya, Dreschsler, and Schnabl, 2013). Thus, regardless of the origin of the crisis, European banks' exposure to sovereign credit risk has been apparent at least since late 2008.

Banks are exposed to the domestic sovereign risk through a number of channels (see, e.g., Committee on the Global Financial System [CGFS], 2011). Furthermore, they are also exposed to the credit risk of non-domestic sovereigns. This is because, for example, they hold a substantial share of the sovereign debt of other countries (Bolton and Jeanne, 2011). The banks' cross-border holdings of sovereign securities can end up strengthening the link among European sovereigns (Korte and Steffen, 2014). Indeed, Ang and Longstaff (2013) show that, already during the global financial crisis, an important fraction of European sovereign credit risk was systemic. In the event that two or more large sovereigns default, the risk of the break-up of the Eurozone becomes concrete. Some banks are likely to be particularly exposed to this risk, either due to large direct exposures, or due to indirect exposures resulting from funding mismatches or risky business models. In contrast, other banks might be more exposed to the credit risk of the domestic sovereign. Distinguishing the source of banks' sovereign exposure is important for designing and implementing adequate policy measures to break the tight bank-sovereign nexus (e.g., Draghi, 2012).

The primary goal of this paper is to quantify the fraction of bank credit risk that is due to sovereign credit risk. Furthermore, we also aim to shed light on the types of sovereign exposure that drive banks' credit risk. Thus, we decompose bank sovereign exposures into a country-specific component, which reflects the probability that the domestic sovereign defaults in isolation (Country Risk), and a systemic component, which reflects the probability that two or more sovereigns will default at the same time (Joint-Sovereign Risk or Euro Area Tail Risk). We do this by developing a multivariate credit risk model that we estimate on the term structures of sovereign and bank credit default swaps (CDS). In order to identify banks' exposures to sovereign risk, we estimate the model in two stages. In the first stage, we model the credit risk of Germany, France, Italy, and Spain over the 2008-2013 period. By focusing on this small but pivotal group of systemically important countries for the Eurozone, we aim to identify a particularly severe joint-sovereign shock that likely not only generates a dramatic drop in the Eurozone's real activity, but also triggers eventually the break-up of the Eurozone itself. Also note that the great majority of systemically important European banks is located in these countries.

In the second stage, we model bank credit risk. We assume that banks can default either in conjunction with a sovereign credit event, triggered by Euro area tail risk and/or country risk, or in isolation. We therefore estimate for each bank its exposure to joint and country sovereign risk, resulting from the first-stage estimation, as well as its idiosyncratic intensity of default. We organize the analysis around a group of reasonably large banks, similarly, for example, to Beltratti and Stultz (2012). Our sample consists of 21 banks, covering roughly three-fourths of euro-banking assets. Crucially, the sample of banks is rather homogeneous, being roughly equally split across countries, so that we can draw comparisons across countries and explore cross sectional differences.

Model estimates only reflect the information embedded in CDS premia and therefore, reveal the market's assessment of banks' exposures to sovereign risk. Thus, they can capture not only the *direct* exposures of individual banks to sovereign risk, resulting from their holdings of European sovereign debt, but also their *indirect* exposures. For example, banks with fragile business models might be indirectly exposed to the sovereign debt crisis irrespective of their holdings of sovereign securities. The strength of the government supports might also determine the banks' exposure to sovereign risk, and in particular to the solvency of the domestic sovereign, as suggested, for example, by Correa et al. (2014). Therefore, we examine what drives the market assessment of banks' sovereign exposures. We do this by regressing the cross section of the estimated sovereign exposures on a number of standard variables, such as bank size, the rating 'uplift' (i.e., the expected government support), the direct holdings of sovereign debt, and the associated sovereign subsidy.

A number of interesting results emerge from our empirical analysis. *First*, the first-stage estimates capture well the evolution of sovereign risk and its components in the Euro area. The main turning points are clearly associated with major political and macroeconomic events that took place in the Euro area and mark four distinct phases. Euro area tail 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 (OMT). Thus, during the OMT phase, the market is no longer perceiving the risk of break-up for the Eurozone. However, it is apparent to see the fragility of Spain and Italy during the period, as they are the countries most exposed to Euro area tail risk. In fact, they have six times higher probabilities than Germany to default in the event of a joint-sovereign shock. France's exposure is about two and half times higher than Germany. However, while in Italy and Spain sovereign credit risk is equally, on average, due to joint and country risk, in Germany and France it is largely driven by joint-sovereign risk.

Second, 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, it also shows significant variation over time. Specifically, joint-sovereign risk explains the largest fraction of French banks' credit risk (30%), which can reach a sample maximum of 81%. In contrast, it 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. We also find that country risk explains a substantial fraction of Spanish, Italian, and French banks' credit risk, and a small but significant fraction of German banks' credit risk. Of particular interest is the comparison of bank and sovereign exposures. Italian and Spanish banks' exposures to both components of sovereing risk are lower than the sovereign exposures of the domestic sovereigns. This result, therefore, shows the sovereign nature of the crisis and again highlights the pivotal role played by the Italian and Spanish sovereigns. In contrast, German and French banks have higher exposures to both types of sovereign shocks than the domestic sovereigns. Thus, the solidity of the sovereigns contrasts with fragility of the banks in Germany and France, which might partly reflect banks' large exposures to pheripheral Europe (Noeth and Segupta, 2012).

Third, although there is a clear country element in banks' exposures to sovereign risk, banks located in the same country still display important differences. Indeed, our cross-sectional analysis show that: (i) the share of bank credit risk that is attributable to sovereign risk increases with bank size; (ii) the fraction of a bank's joint-sovereign credit risk increases with the bank's holdings of non-domestic sovereign debt and with the associated non-domestic subsidy; (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; and (iv) the higher the expected government support for a bank is, the higher its probability of defaulting is when a country sovereign shock arrives. Thus, the market's assessment of banks' exposures to sovereign risk is consistent with the information provided by standard measures of sovereign exposures. In particular, bank size stands out as one of the most satisfactory variables able to explain the fraction of bank credit risk that is due to sovereign risk. Yet, these standard measures, the holdings of *foreign* sovereign debt in particular, fail to explain a significant part of the cross-sectional variation in the estimated exposures, and thus seem to provide a consistent but partial picture of the *overall* exposure of banks to sovereign risk, as perceived by the market.

Finally, the decomposition of bank credit risk we presented so far is based on the intensities of default, which are of particular interest as they capture the instantaneous credit (or default) risk of banks. Two further effects, however, can help better characterize the market's assessment of bank exposures to sovereign risk. First, we can assess how the decomposition of bank credit risk varies with the horizon. We find that the fraction of German and French banks' credit risk that is due to sovereign decreases with the horizon. In fact, at the 10-year horizon it is roughly half of that at the 1-year horizon. In contrast, for Italian and Spanish banks, it is rather stable over time. When looking at the components of sovereign risk, however, we find that Euro area tail risk is largely priced in the short-to-medium term CDS contracts, and thus is perceived by the market as a short-run risk relative to country risk. Second, we can examine the role of distress risk premia by decomposing the CDS contracts, which reflect both changes in credit risk and default risk premia, into the sovereign and bank-specific components. The magnitude of the effect is somewhat striking. The component of bank CDS due to sovereign credit risk can be as high as 60%. Moreover, given that sovereign risk commands higher risk premia than idiosyncratic bank risk and risk premia generally increase with the horizon, the longer-term bank CDS reflects a larger component of sovereign risk. We can therefore conclude that the fraction of bank credit risk due to sovereign risk that is constructed from the intensities of default represents a lower bound, given the reinforcing effects of the horizon and of the distress risk premia.

Related Literature. Our findings contribute to the ongoing policy debate about the drivers of bank exposures to sovereign risk, and the implementation of adequate measures to break the tight link (Van Rompuy et al., 2012; Draghi, 2012; Mersch, 2013; Angelini, Grande and Panetta, 2014). This issue has also inspired a number of largely theoretical academic studies. For example, 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 and, in particular, provide novel evidence on the transfer of credit risk from banks to sovereigns. 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 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 joint-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 unifying quantitative framework for assessing banks' exposures to sovereign risk.

Turning to the model specification, 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, in our model, bank credit risk is driven by three separate default intensities: two are related to sovereign risk, and one is bank-specific. In this regard, although our multivariate model is estimated on single-name CDSs, the model setup resembles the three-factor portfolio credit models of Longstaff and Rajan (2008) and Bahansali, Gingrich, and Longstaff (2008). In contrast, most of the earlier studies are organized around univariate reduced-form models, and thus do not model directly the systematic component of credit risk.[1] In addition, similarly to Pan and Singleton (2008), we model the behavior of bid-ask spreads, to account for time-varying and maturity-specific liquidity effects. In this way, changes in default intensities are largely driven by credit risk, as opposed to (il)liquidity, for example.

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; Bisias et al., 2012). 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 systematic vulnerability for banks. Other standard sources of risk that may have a systematic nature and pertain to banks but not to sovereigns relate for example to regulation, funding, liquidity and monetary policy (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 co-move substantially; this confirms that (i) those alternative sources of systematic risk are empirically relevant, and (ii) our model is successful in separating them from the component that is directly associated with sovereign risk. Finally, our study also relates to the increasing number of studies focusing on the Eurozone's debt crisis and the role of European banks in particular (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; Pagano and Sedunov, 2014; Xu et al., 2014; Battistini, Pagano, and Simonelli,

[1] Notable examples are Duffie and Singleton (1999), Driessen (2005), Pan and Singleton (2008), and Longstaff et al. (2011).

2014).[2]

The remainder of the paper is organized as follows. Section 2 builds up our model. Section 3 presents the CDS data and discusses the econometric method and model fit. Section 4 discusses the sovereign credit risk estimates, whereas Section 5 focuses on the estimates relative to bank credit risk and presents a detailed cross-sectional analysis of bank exposures to sovereign risk. Section 6 assesses the term structure and distress risk premium effects. Finally, Section 7 concludes the paper.

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. If we assume that the premium is paid continuously, the present value of the premium leg of a credit default swap is given by:

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

[2] Of particular note is the recent study of Xu et al. (2014), which also uses CDS spreads to capture the joint likelihood of extreme events for European sovereign and bank entities. And, it also does this by shifting the focus away from the capital structure adopting a reduced-form approach. However, our study differs from their for a number of reasons, two worth of mention. First, we rely on a pricing model that exploits the information embedded in the whole term structure of CDS spreads. This, in turn, allows us to shed light on the market perception of the sources of bank credit risk (sovereign systematic and country-specific and bank-specific) at different horizons. Second, we uncover to what extent estimates of bank sovereign exposures implied in asset prices relate to standard measures used, for example, in policy circles.

where r_t is the instantaneous default-free interest rate, and λ_t is the intensity of a credit event. 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, $P(CDS, t, M)$:

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

In the empirical analysis, 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.* $R^{\mathbb{Q}} = 0.50$.[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/sovereign-specific shocks. Second, sovereigns can experience joint defaults, so that there is a common intensity that jointly determines their credit risk. Thus, during a joint-sovereign credit shock every sovereign can eventually default, but sovereigns' exposures

[3] Ang and Longstaff (2013), among others, also assume a risk-neutral loss given default (LGD) of 50%. However, there is not a clear consensus about its value. For example, Liu (2014) shows that a 60% LGD is rejected for most of the corporate issuers condidered, suggesting instead a lower value. However, the specific value assumed for the LGD should not substantially affect our estimates of the intensity weights (see, Li and Zinna, 2014), and their cross sectional dispersion across banks, which is ultimately the main focus of this study.

to this common event can differ. Specifically, sovereign i's default intensity is composed of the country intensity ($C_{t,i}$) and the scaled joint 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 joint-sovereign 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 'joint' and 'country specific'.[4]

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.[5] 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

[4] Ang and Longstaff (2013) use a similar model and term the probability of joint sovereign defaults as sovereign systemic risk. There is, however, 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 therefore refer to the joint defaults of sovereigns as either joint-sovereign risk, or systematic sovereign risk, or Eurozone tail risk. Given that we only include large sovereigns, a joint default is likely to trigger the break-up of the Euro zone, so in some circumstance we might also refer to S_t as to Euro area break-up risk. However, for our analysis, regardless of the term used, the crucial point though is to disentangle this event from country-specific sovereign risk.

[5] The squared-root process is particularly suitable for modeling 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, 2014).

credit shocks. In particular, banks are exposed to joint-sovereign credit risk and to the 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* joint-sovereign 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 joint and country-specific 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:

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

where $\eta_{i,j}$, $\kappa^{\mathbb{Q}}_{i,j}$, and $\sigma_{i,j}$ are the constants and the Brownian motion is now $Z^{\mathbb{Q}}_{t,i,j}$, which is independent of $B^{\mathbb{Q}}_t$ and $W^{\mathbb{Q}}_{t,i}$.[6]

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

[6]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; Li and Zinna, 2014). However, this comes at the cost of not being able to study the transmission of shocks, or contagion, among the S_t, $C_{t,i}$ and $I_{t,i,j}$ intensities. 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 Euro area tail risk (S_t).

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 joint, 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.[7]

3 Model Estimation

In this section, we first present the CDS data to be used for model estimation and empirical analysis. We then turn to describing the econometric methodology, a detailed description of which is presented in the Internet Appendix. We conclude the section with the parameter estimates and model-fit statistics.

3.1 The Data

3.1.1 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.[8] The severity of such an event, regardless of where it originates, likely not only generates a dramatic drop in real activity, with the Eurozone economy sinking into a

[7] 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 implies that a series of non-linear constraints must be implemented in the estimation. Imposing 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.

[8] We do not include the UK as the focus of the analysis is on the tight link between banks and sovereigns within the Eurozone.

recession, but also eventually triggers the tail risk of a breakup of the Euro area. Of interest is that, despite being a small group of countries, 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 by country groups, especially with regard to their exposures to joint and country sovereign credit shocks.

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.[9] 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 billion, for which a sufficiently liquid term structure of CDS premia is available. Furthermore, we try not to include subsidiaries, with only few exceptions, so that in the subsequent analysis we can use the rating uplift to measure the expected government support. 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.

3.1.2 The Term Structure of CDS

The data for this study include the term structures of sovereign and bank CDS spreads for the 1-, 3-, 5-, 7- and 10-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

[9] 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.

the most liquid contracts.[10] 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.[11] Our sample is therefore of particular interest as it covers both the 2008-2009 global financial crisis and the bulk of the Euro debt crisis.

Table 1 presents summary statistics of the five-year CDS mid quotes. There is substantial cross-sectional variability in the average credit risk of the banks within each country. However, 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.

The average term structures of the CDS mid quotes are generally upward sloping. This stylized fact contrasts with the inspection of the bid-ask average term structures, which are generally either downward sloping or concave. Thus, market liquidity seems to vary remarkably across maturities. If 5-year CDS contracts are particularly liquid, liquidity is particularly scarce at the 1-year maturity and (although somewhat less) at the 10-year maturity. For the German and Spanish sovereigns, however, the 1-year bid-ask spreads are of comparable magnitude to those of the other maturities. Overall, sovereign CDS contracts are generally more liquid than bank CDS contracts.

[10]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.

[11]CMA database quotes lead the price-discovery process in comparison with the quotes provided by other databases (Mayordomo, Peña and Schwartz, 2010). Specifically, CMA consensus data (bid, ask and mid) are sourced from 30 buy-side firms, including major global investment banks, hedge funds, and asset managers. The other widely used provider for CDS data is Markit. Their CDS quotes are also contributed by 30 major market participants. Then, the quotes are translated to a composite spread, through a Markit's algorithm. For this reason, the spreads provided by Markit reflect both quotes and realized transactions. However, the comparison of CMA spreads with Markit spreads for our sample of sovereigns and banks reveals that the difference is negligible for the 5-year contracts. The difference instead consists of few basis points for the remaining maturities, and tend to increase somewhat as liquidity deteriorates. But our model specification allows for maturity specific time-varying measurement errors.

3.2 Econometric Framework

We implement a two-stage estimation procedure, which is instrumental to determine banks' exposures to sovereign credit risk.[12] In the *first stage*, we estimate the sovereign multivariate credit risk model – described in Section 2 – on sovereign CDS premia. In order to separate the joint-sovereign intensity from the country-specific intensities, the estimation is performed jointly for all sovereign entities. Recall that the joint-sovereign intensity enters the pricing of all sovereign CDS premia. Two identifying restrictions are required. First, we normalize the German exposure to the intensity S_t to unity ($\alpha = 1$), which effectively rescales the other sovereigns' exposures. As a result, α_i indicates the probability that sovereign i defaults, relative to the probability that Germany defaults, in the event of a joint-sovereign shock. Second, differently from Ang and Longstaff (2013), we allow Germany to default not only in the event of a joint-sovereign shock, but also in the event of a sovereign-specific shock. In this way, in line with the other countries, we can investigate the exposure of German banks to the credit risk of the domestic sovereign. Thus, in the first-stage we estimate the sovereign intensities S_t and $C_{t,i}$, as well as the parameters driving their risk neutral dynamics $\theta^{\mathbb{Q}} = [\eta, \kappa^{\mathbb{Q}}, \sigma]$ and $\theta_i^{\mathbb{Q}} = [\eta_i, \kappa_i^{\mathbb{Q}}, \sigma_i]$; the sovereign exposures (α_i); the objective mean reversion parameters $\kappa^{\mathbb{P}}$ and $\kappa_i^{\mathbb{P}}$, which enter the market prices of risk; and, the parameters $\sigma_{\epsilon,i}$ entering the pricing-error volatilities.

In the *second-stage*, we perform a bank-by-bank estimation. Specifically, conditional on the first-stage estimates of the intensities S_t and $C_{t,i}$ and of the parameter blocks $\theta^{\mathbb{Q}}$ and $\theta_i^{\mathbb{Q}}$, we estimate separately for each bank (i, j) its latent intensity $I_{t,i,j}$; the associated risk-neutral parameters $\theta_{i,j}^{\mathbb{Q}} = [\eta_{i,j}, \kappa_{i,j}^{\mathbb{Q}}, \sigma_{i,j}]$; the objective mean reversion $\kappa_{i,j}^{\mathbb{P}}$; the joint, $\alpha_{i,j}$, and

[12] 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 (2014), we would expect that a joint (one-stage) estimation of the model would result in the bank-systemic and bank-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 joint intensity was different but individual bank exposures' to the joint 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.

country-specific, $\gamma_{i,j}$, sovereign exposures; and, the parameter $\sigma_{\epsilon,i,j}$ driving the pricing error volatility. In this second stage, no further identification restriction is required. Bank exposures to joint-sovereign 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 joint-sovereign shock. Similarly, the country 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.

A natural way to proceed is to cast our multivariate credit risk model into a state-space framework by discretizing the continuous-time dynamics using a standard Euler scheme and to use a Bayesian method to implement estimation. An important feature of our model, however, is that we specify the variance of the CDS pricing errors as function of market (il)liquidity. In this way, our estimates of the default intensities should largely reflect credit risk, being less affected by changes in market liquidity (Pan and Singleton, 2008). Taking for example of sovereign i, we assume that the CDS contract of maturity M is 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 $\sigma_{\epsilon,i}$, which is common across maturities, measures the degree of model mispricing relative to the observed bid-ask spreads. In this way, the pricing-error variances vary over time and across maturities with the bid-ask spreads.

Although this specification is rather parsimonious, it is able to account for the fact that market liquidity varies over time and across maturities. In essence, 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. These are times when liquidity drops and bid-ask spreads consequently widen.[13] Putting simply, when market liquidity drops, bid-ask spreads widen and so does the variance of the pricing errors, so that the intensities of default will not try to match temporary changes in the CDS premia which are due to liquidity effects. Using this specification, we can include in the analysis short-term contracts which, although might be less liquid, are likely to be very important to help identify the sovereign risk components. Short term contracts tend to promptly react to episodes of strongly enhanced

[13] Of course, bid-ask spreads alone cannot capture the multiple facets of (il)liquidity. This concern though is partly attenuated by the fact that changes in bid-ask spreads are mapped onto the measurement errors through the $\sigma_{\epsilon,i}$ parameter.

risk, which can eventually result in the inversion of the term structure.

We propose a Bayesian estimation method, which builds on the algorithm developed by Li and Zinna (2014). We use a hybrid MCMC algorithm that combines the Gibbs sampler with a series of slice-sampling steps (Neal, 2003), as it is not feasible to sample directly from the posterior distributions of the parameters entering the CDS pricing. 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 distributions. The priors used in this study are diffuse and their distributions are chosen for convenience following a number of earlier papers (e.g., Johannes and Polson, 2009). The above method allows us to simultaneously estimate model parameters and latent factors and account for the uncertainty around the estimates. We can, for example, easily quantify the noise that first-stage estimates induce entering the second-stage estimation (see the Internet Appendix for the detailed algorithm).[14]

3.3 Parameter Estimates and Model Fit

We now present the parameter estimates and discuss the model fit. Table 2 reports the estimates of the parameters driving the joint (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 the 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

[14]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.

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. The systematic 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. In general, 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 is in part due to its relatively low liquidity, as also reflected by its relatively large bid-ask spreads.

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 joint 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 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.

4 Sovereign Credit Risk

4.1 Euro Area Tail Risk, S_t

Figure 1 presents the time-series estimate of the joint-sovereign intensity (S_t) with the 95% credible intervals, showing that the intensity is estimated very precisely. It is evident that four distinct phases characterize the evolution of joint-sovereign risk and that the main turning points are largely associated with a few political events (dotted lines), which mostly pertain to the Eurozone.[15]

The first phase spans the 2008-2009 financial crisis. After an initially subdued response to the onset of the financial crisis, joint-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 Euro area tail risk. The intensity S_t 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, S_t reaches its sample maximum in November 2011. The many measures undertaken by the European authorities, such as the Longer-term Refinancing Operations (LTRO) and the fiscal pact, might have helped attenuate the unprecedented rise in S_t. However, only with Mario Draghi's "Courageous Leap" speech in May 2012, the "Whatever It Takes" speech in

[15] 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).

July 2012, and the introduction of the Outright Monetary Transactions (OMT) in August 2012 does Euro tail risk 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 the market no longer pricing Euro sovereign tail risk, i.e., S_t takes negligible values.

4.2 Sovereign Exposures to Euro Area Tail Risk, α_i

We now turn to the *cross-sectional* dimension of sovereign risk. Table 2 presents the estimated sovereign exposures (α_i). Recall that α_i denotes the ratio of the conditional probability of default of sovereign i to that of Germany in the event of a joint-sovereign shock. France has an exposure of 2.56, indicating 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 joint-sovereign shock. Italy and Spain display the highest exposures of about 6.0. However, not only do Italy and Spain display the highest exposures, but the S_t intensity also reaches its highest values in the summer of 2011. This evidence well accords with the anecdotal evidence suggesting that the tensions in the Euro area became systemic in the summer of 2011 as they spread to the Italian and Spanish government securities (Angelini, Grande, and Panetta, 2014).

The exposures α_i's seem to largely reflect the credit risk of the sovereign, as proxied, for example, by the average five-year CDS spread over the period. This point is also noted by Li and Zinna (2014). We therefore complement the analysis by looking at the sovereign *systematic intensity weight* (SIW), *i.e.* $\alpha_i S_t/(\alpha_i S_t + C_{t,i})$, whereby joint-sovereign risk is standardized by the total risk of the sovereign, and is, therefore, comparable across sovereigns with different levels of credit risk. The bottom panel of Table 2 shows that the ordering of the systemically important sovereigns changes remarkably when moving from the systematic exposures to the SIWs. In fact, the systematic 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.

Our results differ from those of previous studies. Ang and Longstaff's (2013) find substantially lower exposures for France, Italy, and Spain (0.93, 1.71, and 1.51, respectively). In addition, their sovereign systemic intensity reaches its peak in the 2008-2009 crisis, while it takes much lower values when the crisis evolves into a sovereign debt crisis. Moreover, in their study, the behavior of the European sovereign systemic intensity strongly mirrors that of the US. 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 not surprising given that they focus on a much shorter sample, which is dominated for two-thirds by the 2008-2009 crisis.[16] More fundamentally, our estimated joint-sovereign intensity is also remarkably different from the systemic *bank* intensity presented by Li and Zinna (2014), which is estimated separately on a panel of seven large US and UK banks, over a similar time period. In fact, their intensity reaches its peak during the 2008-09 global financial crisis, and takes much lower numbers thereafter during the Eurozone sovereign debt crisis. 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 systematic risk of the Eurozone sovereigns.

4.3 Country Risk, $C_{t,i}$

Figure 2 shows the country sovereign intensities ($C_{t,i}$) along with the *scaled* joint-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 systematic component until the drop in systematic risk following the "Whatever It Takes" speech by Mario Draghi. The evolutions of the French $\alpha_i S_t$ and $C_{t,i}$ intensities 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.

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

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

the four phases which characterize our sample. For example, the increase in Italian country credit risk during the second phase, starting with the first bailout package for Greece, is limited, while the rise in Spain's credit risk is instead equally due to $\alpha_i S_t$ and $C_{t,i}$. At the start of the third phase in the summer of 2011, a sudden increase in Italian country credit risk leads the remarkable increase in joint-sovereign credit risk. In contrast, around this time, joint-sovereign risk is the main driver of the rise of Spanish CDS spreads. Then, when Greek parliament passes the austerity bill in February 2012, the remarkable, but temporary, drop in $\alpha_i S_t$ is partly offset in Italy and completely in Spain by an increase in $C_{t,i}$. However, in the aftermath of the second speech by Mario Draghi, the drop in Italian and Spanish CDS spreads is driven by both components.

5 Banks' Exposures to Sovereign Risk

5.1 Decomposing Bank Credit Risk

Figure 3 shows the decomposition of bank credit risk into the sovereign components and the bank idiosyncratic component (by country averages). A few considerations are in order. First, at the start of the 2008-2009 crisis, bank credit risk is largely idiosyncratic. Then, as the crisis deteriorates with Lehman's bankruptcy and the European governments put in place system-wide measures to try to rescue the banking sectors, sovereign risk picks up. 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 (dotted lines in Figure 3). Of further note is that the increase in sovereign risk, which is largely common across countries, and is therefore reflected in the Euro area tail risk component, is associated with a drop in the bank-idiosyncratic intensities (Figure 4). This is particularly evident for French, Italian and Spanish banks, while bank idiosyncratic credit risk is still rising, although at a lower pace, in Germany. Therefore, our findings are consistent with the timeline suggested by Acharya, Dreschsler, and Schnabl (2013).[17]

[17]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

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 risk explains a large fraction of banks' credit risk starting as early as October 2008. Country sovereign credit risk only begins to play a significant role in explaining German and French banks' credit risk in late 2009.

In sum, we find evidence of the transfer of credit risk from banks to sovereigns. However, this is a particularly short-lived episode, concentrated in the period soon after the introduction of the system-wide rescue programmes. 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, either due to Euro area or country risk, affecting the solvency of banks.

However, 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.[18] This implies that if the first-stage estimation accurately captures sovereign risk instead of bank credit risk, then the bank *idiosyncratic*-intensities of default, $I_{t,i,j}$, 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 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 principal components behave as level factors, as they load

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.

[18]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.

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 sovereign intensities displayed in Figure 2.

5.2 Bank Sovereign Exposures

Table 3 presents the estimates of individual bank exposures to joint and country sovereign risk. We also report the country averages of the bank exposures. Recall that systematic 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 systematic sovereign shock (S_t). The average systematic 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 exposure of the average Italian bank to Euro area tail risk is substantially lower (1.95). The average exposure of French banks is also particularly high (2.84).

Nevertheless, riskier banks tend to have higher $\alpha_{i,j}$ 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 sovereign systematic 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 systematic risk, on average, only explains 11% of banks' credit risk, reaching a maximum of 39%.[19] Euro area tail 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

[19]Note that this result for Italian banks is largely driven by Intesa Sanpaolo and Unicredit, which display null exposures to Euro area tail 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.

average country exposures at 0.54 and 0.56, respectively. However, Figure 2 reveals that the German and French country 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 accounts for 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 types of sovereign risk.

5.3 What Drives Market-based Bank Sovereign Exposures?

Thus far, we carried out a rather descriptive analysis of our market-based estimates of bank exposures to sovereign risk. In particular, we grouped the banks by their country of residency. However, although there is a clear country element in banks' exposures to sovereign risk, banks located in the same country still display important differences. A natural question then is: what drives the cross-sectional variation in the estimated SIW and CIW? A number of measures have been put forward to try to capture banks' (largely) direct exposures to sovereign risk. In the subsequent analysis, we focus on some of the most widely used, such as: bank size, holdings of domestic and non-domestic sovereign debt, the associated sovereign domestic and non-domestic subsidies. We also examine the link between banks' exposures to country risk and the expected government support.

5.3.1 Bank Size and Holdings of Sovereign Debt

Indicators of financial institutions' systemic exposures, such as the SRISK,[20], 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.[21] In fact, the largest institutions generally score also as the most systemically important institutions. However, larger banks might also be more exposed to sovereign risk. They 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). Also note that 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).[22]

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 sovereign 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 sovereign exposure measure. This clearly occurs in our case, as our measures of sovereign 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).[23]

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

[21]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).

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

[23]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 systematic (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). In contrast, the $\alpha_{i,j}$ 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 systematic crisis, and additional

We measure bank size in terms of the total assets of the bank relative to domestic GDP.[24] Interestingly, we find that bank size is statistically significant at the 5% with R-squared of 19% in the SIW regression (Panel B), and at the 1% with R-squared of 37% in the CIW regression (Panel C).[25] When we look at the total fraction of bank credit risk which is due to sovereign risk (SIW+CIW), we find that size explains roughly half of the cross-sectional variation (Panel A). Therefore, the fraction of bank credit risk due to sovereign credit risk increases with bank size, so that larger banks are more intimately linked to sovereign risk, as also suggested by Laeven, Ratnovski and Tong (2014). In contrast, smaller banks display higher average CDS premia, and their credit risk is largely bank specific. Of further interest is that size is more important in explaining the fraction of bank credit risk due to country rather than joint-sovereign risk.[26]

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, 2014). 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.[27] Indeed the premise seems to be supported by the

controls would be needed. 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.

[24]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.

[25]Note that, in the cross sectional regressions, we use the heteroskedatic-consistent standard errors of White (1980) to account for the fact that we use generated dependent variables, i.e. they are based on the estimates resulting from the multivariate credit risk model.

[26]Note that we also experimented with capital ratios, finding that, regardless of their measurement, do not correlate either with SIW or CIW.

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

data: SIW and CIW increase in the bank holdings of foreign and domestic sovereign debt, respectively (Table 4). To complete the analysis, we relate the *aggregate* holdings of sovereign debt to SIW+CIW. The estimated effect is statistically significant at the 1%.

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 increasingly links the banks to the outlook not only of the domestic sovereign but also of the Eurozone as a whole.

Therefore, we test whether the domestic and non-domestic sovereign subsidies relate to CIW and SIW. The domestic and non-domestic subsidies are measured 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.[28] 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).[29]

Thus far, we established that market-based measures of sovereign exposure – SIW and CIW – move consistently with standard measures of sovereign exposure. However, our cross-sectional analysis is organized around a series of univariate regressions. This is largely due to the relatively small cross section of banks and the somewhat correlated regressors. The use of a limited number of regressors, however, is likely not to be particularly problematic when using SIW and CIW, as they are comparable across banks of different riskiness. For this reason, we can base the analysis on a smaller number of controls.

[28]We refer to Appendix D in Korte and Steffen (2014) for the detailed description of the methodology.

[29]We standardize the holdings of sovereign debt and the subsidy by the country GDP, however, the results are qualitatively robust if we use non-standardized variables.

However, it is clearly important to establish whether the size effect prevails over the direct exposure effect, i.e., resulting from the bank holdings of sovereign debt. We therefore complement the analysis by including both bank size and the holdings of sovereign debt (or the sovereign subsidy) in the same regression. The size effect seems to dominate in the SIW+CIW regression. However, it is less precisely estimated, and the holdings of sovereign debt and the subsidy are still correctly signed. Moving to the individual SIW and CIW regressions, the results are somewhat different. In the SIW regression, although the two effects are correctly signed, they are no longer statistically significant. In contrast, both effects are statistically significant in the CIW regression. Of further note is that (SIW) CIW does not increase with the holdings of domestic (foreign) sovereign debt (not reported). Similar results hold for the sovereign subsidy.

These results, taken together, suggest that (i) bank size is indeed an important determinant of banks' exposures to both types of sovereign risk, while the holdings of sovereign debt (and the associated subsidy) help explain country risk; (ii) these variables explain roughly half of the cross-sectional variation in the estimated bank sovereign exposures; (iii) it is, however, more difficult to explain bank exposures to Euro area tail risk.

5.3.2 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. In turn, this 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 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).[30]

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 5%. This evidence 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. We then replace bank financial strength with size as a control, also in light of the considerations of Section 5.3.1. The uplift is still statistically significant at the 5%, and size is also positively signed and statistically significant at the 10% (not reported).[31]

We then repeat the analysis by replacing the γ exposures with the CIWs as dependent variables. 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 risk. The results change considerably (Table 5,

[30] 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. 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.

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

right panel). 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%.

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.

6 Term Structures and Distress Risk Premia

The decomposition of bank credit risk we presented so far, i.e., the SIWs and CIWs, is based on the intensities of default. The intensity of default is of particular interest for a number of reasons. First, it summarizes the information contained in the entire term-structure of CDSs. In contrast, CDS contracts of specific maturities tend to be contaminated by microstructure effects. In addition, the intensity of default reflects the probability to default in the next instant, rather than long-term averages, which are instead implied in CDS contracts. For this reason, it is particularly responsive to changes in credit risk, and is a direct measure of credit (default) risk, not being affected by distress risk premia, which are instead embedded in CDS contracts.[32] As a result, in this section, we examine two further effects which might be important to better understand the sovereign exposure of banks. First, we perform the decomposition of bank credit risk at different horizons. Second, we repeat the decomposition of bank credit risk, at different horizons, but taking into account also the effect of the distress risk premia.

In order to look at the effect of maturity, while still excluding the risk premium effect, we first compute the objective CDS(M)$^{\mathbb{P}}$ price for different maturities. We then decompose the CDS$^{\mathbb{P}}$ of the generic bank (i, j) for maturity M into the three components: SIW$^{\mathbb{P}}$(M), CIW$^{\mathbb{P}}$(M) and BIW$^{\mathbb{P}}$(M). Note that, if M equals an infinitesimal time period, one week in our

[32] 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; Zinna, 2013). As a result, CDS premia reflect both credit risk (or default risk) and distress risk premia.

study, then the resulting quantities will be the intensity weights SIW, CIW and BIW. Figure 5 presents the term structure of the fraction of bank credit risk which is due to sovereign risk for different horizons ($\text{SIW}^{\mathbb{P}}(\text{M}) + \text{CIW}^{\mathbb{P}}(\text{M})$). It is apparent that the share of sovereign risk tends to decrease with the maturity for German and French banks; in fact, at the 10-year horizon it is about half than at the 1-year horizon. In contrast, for Italian and Spanish banks, $\text{SIW}^{\mathbb{P}}(\text{M}) + \text{CIW}^{\mathbb{P}}(\text{M})$ is rather stable across maturities.

We now turn to examining the effect of the distress risk premia. We do this by presenting the decomposition of the (risk-neutral) CDS prices: $\text{SIW}^{\mathbb{Q}}(\text{M})$, $\text{CIW}^{\mathbb{Q}}(\text{M})$ and $\text{CIW}^{\mathbb{Q}}(\text{M})$. The resulting evidence is clear-cut. When we account also for the effect on the risk premia, the impact of sovereign risk is substantially higher, and tend to increase with the horizon. For Italy and Spain, it increases monotonically, so that at the 10-year maturity the sovereign component accounts for roughly 55% of bank CDS spreads. For Germany and France, it reaches its peak around the 6-year maturity, being 40% and 60%, respectively. This effect is due to the fact that the distress risk premium component associated with sovereign credit risk is substantially higher than that associated with bank-idiosyncratic credit risk. This result is not surprising given that sovereign credit risk is systematic, whereas investors can more easily diversify the idiosyncratic credit risk of banks. The shape of the $\text{SIW}^{\mathbb{Q}}(\text{M})+\text{CIW}^{\mathbb{Q}}(\text{M})$ curve ultimately depends, on the fraction of bank credit risk which is due to joint and country-specific sovereign credit risk. We address this issue next.

Figure 6 shows the sovereign $\text{SIW}^{\mathbb{P}}(\text{M})$ and $\text{SIW}^{\mathbb{Q}}(\text{M})$. A number of results emerge. According to $\text{SIW}^{\mathbb{P}}(\text{M})$, joint-sovereign risk is largely perceived by the market as a short-to-medium term risk. This effect is intensified by the distress risk premia: in fact, $\text{SIW}^{\mathbb{Q}}(\text{M})$ falls with the horizon quicker than $\text{SIW}^{\mathbb{P}}(\text{M})$. Of further interest is that $\text{SIW}^{\mathbb{P}}(\text{M})$ lies above $\text{SIW}^{\mathbb{Q}}(\text{M})$ for Germany and France, whereas the opposite is true in Italy and Spain. This contrasting evidence between core and peripheral countries can be rationalized as follows. First, the term structure of joint-sovereign risk premia is hump shaped, whereas country-specific risk premia slope upward - see the Internet Appendix for a detailed analysis of the risk premia. Second, although the credit risk of Germany and France, as shown in Section 4, is largely due to Euro area tail risk (SIW), the risk premium associated with country risk is also particularly high.

In sum, the fraction of bank CDS due to sovereign credit risk can be as high as 60% when the effect of distress risk premia is taken into account.[33] Moreover, given that sovereign risk commands high risk premia, and risk premia generally increase with the horizon, longer-term bank CDS reflect a larger component of sovereign risk. However, Euro area sovereign risk is largely priced in shorter-term CDS contracts. This finding, coupled with the evidence on the drop of the joint-sovereign intensity during the OMT period, lends support to the choice of the ECB to tackle the break-up risk of the Eurozone by focusing the OMT on government-issued bonds with short maturities.

7 Conclusions

In this study, we uncover novel evidence on the exposure of large banks to sovereign risk by only using publicly available information. We do this by estimating a multivariate credit risk model on the term structures of sovereign and bank CDS premia for the 2008-2013 period. We focus on the Eurozone which serves as a natural laboratory to examine the bank-sovereign nexus. We look at the banks located in two core countries, Germany and France, and two peripheral countries, Italy and Spain. The great majority of systemically important European banks is located in these countries.

We find that sovereign risk accounts for about 45% of French and Spanish bank credit risk, and 30% and 23%, respectively, of Italian and German bank credit risk. However, while Italian banks are particularly exposed to country risk, *i.e.*, the probability that the domestic sovereign defaults in isolation, French and German banks are largely exposed to systematic sovereign risk, *i.e.*, the probability that two or more sovereigns default at the same time. Of particular interest is also that Italian and Spanish banks display exposures to both types of sovereign risk – systematic and country risk – which are smaller than the exposures of

[33] There is novel evidence showing that capital losses of sellers of CDS protection can impact subsequent CDS spreads. Siriwardane (2015) quantifies this effect to account for roughly 10% of the fluctuations in CDS. However, sellers' capital losses should affect CDS spreads through changes in the price of default risk, and, thus, through the distress risk premium component of the CDS. Thus, this effect should not be reflected in our estimates of SIW and CIW which rely on the default intensities. However, it can partly explain why we find that the fraction of bank CDS due to sovereign credit risk increases when the effect of distress risk premia is taken into account.

the domestic sovereigns. In addition, the Italian and Spanish sovereigns display systematic exposures which exceed also those of German and French banks. Thus, these findings show not only the sovereign nature of the crisis in Italy and Spain, but also the central role played by the Italian and Spanish sovereigns in determining Eurozone systematic sovereing risk.

Then, the cross-sectional analysis reveals that our measures of sovereign exposures, which should reflect the market's assessment of the *overall* exposures of banks to sovereign risk, are related to a number of measures which are widely used by academics and policy makers to quantify bank sovereign exposures. In particular, bank size stands out as the most successful measure. In contrast, banks' holdings of sovereign debt, which capture the *direct* exposure of banks to sovereign risk, seem to be of secondary importance, in particular in explaining the exposures of banks to systematic sovereign risk. As a result, direct exposures seem to account only for a small part of the overall exposure of banks to sovereign risk, and thus they provide only a partial assessment of bank exposures to sovereign risk. We also find that the expected government support contributes to make the banks more dependent on the credit risk of the domestic sovereign.

Two further effects, however, are particularly important to better understand the market's assessment of banks' sovereign exposures. First, the market perceives systemic sovereign risk, which can result in the break-up of the Eurozone, to be a short-run risk, as it is largely priced in short-to-medium term contracts. This result, combined with the drop in systematic sovereign risk that we document around the introduction of the OMT, lends support to the choice of the ECB to contrast the unfolding of the Eurozone debt crisis by purchasing short-term sovereign debt. Second, when the effect of the risk premia is also taken into account, we find that sovereign risk can explain as much as 60% of the bank CDS premia. This is due to the fact that sovereign risk, and its systematic component in particular, commands particularly high risk premia; in contrast, idiosyncratic bank credit risk, which is more easily diversifiable by the investors, commands smaller risk premia. We can therefore conclude that, in order to try to capture the complexity of the sovereign exposure of banks, it is important to exploit the information contained in the entire term structure of CDS prices, as well as separate the credit risk component from the credit risk premium component.

All in all, our findings should help the authorities in their attempt to design and implement adequate policy actions to break the tight bank-sovereign nexus (e.g., Draghi, 2012; Van Rompuy et al., 2012).

A Appendix: Pricing Credit Default Swaps

For the pricing of sovereign CDS premia, which is based on a two-factor pricing model, we refer to, *e.g.,* Ang and Longstaff (2013). Next, we present the pricing of bank CDS premia, which is based on three default intensities and is therefore new:

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

$$
\begin{aligned}
\widetilde{\mathbf{I}}(s,S_s,C_{s,i},I_{s,i,j}) &= \mathbf{C}(s,S_s)\mathbf{A}(s,C_{s,i})\mathbf{S}(s,I_{s,i,j}), && \text{(A.4)}\\
\widetilde{\mathbf{C}}(s,S_s,C_{s,i},I_{s,i,j}) &= \mathbf{C}(s,S_s)\mathbf{B}(s,I_{s,i,j})\mathbf{H}(s,C_{s,i}), && \text{(A.5)}\\
\widetilde{\mathbf{S}}(s,S_s,C_{s,i},I_{s,i,j}) &= \mathbf{A}(s,C_{s,i})\mathbf{B}(s,I_{s,i,j})\mathbf{F}(s,S_s), && \text{(A.6)}\\
\mathbf{B}(s,I_{s,i,j}) &= \mathbf{B}_1(s)\exp(\mathbf{B}_2(s)I_{s,i,j}), && \text{(A.7)}\\
\mathbf{A}(s,C_{s,i}) &= \mathbf{A}_1(s)\exp(\mathbf{A}_2(s)C_{s,i}), && \text{(A.8)}\\
\mathbf{C}(s,S_s) &= \mathbf{C}_1(s)\exp(\mathbf{C}_2(s)S_s), && \text{(A.9)}\\
\mathbf{S}(s,I_{s,i,j}) &= (\mathbf{S}_1(s)+\mathbf{S}_2(s)I_{s,i,j})\exp(\mathbf{B}_2(s)I_{s,i,j}), && \text{(A.10)}\\
\mathbf{H}(s,C_{s,i}) &= (\mathbf{H}_1(s)+\mathbf{H}_2(s)C_{s,i})\exp(\mathbf{A}_2(s)C_{s,i}), && \text{(A.11)}\\
\mathbf{F}(s,S_s) &= (\mathbf{F}_1(s)+\mathbf{H}_2(s)S_s)\exp(\mathbf{F}_2(s)S_s), && \text{(A.12)}
\end{aligned}
$$

$$
\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.13)}\\
\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.14)}\\
\mathbf{A}_1(s) &= \exp\left(\frac{\eta_j(\kappa_j^{\mathbb{Q}}+\psi)s}{\sigma_j^2}\right)\left(\frac{1-v}{1-ve^{\psi s}}\right)^{2\eta_j/\sigma_j^2}, && \text{(A.15)}\\
\mathbf{A}_2(s) &= \frac{\kappa_j^{\mathbb{Q}}-\psi}{\sigma_j^2}+\frac{2\psi}{\sigma_j^2(1-ve^{\psi s})}, && \text{(A.16)}\\
\mathbf{C}_1(s) &= \exp\left(\frac{\eta(\kappa^{\mathbb{Q}}+\psi)s}{\sigma^2}\right)\left(\frac{1-v}{1-ve^{\psi s}}\right)^{2\eta/\sigma^2}, && \text{(A.17)}\\
\mathbf{C}_2(s) &= \frac{\kappa^{\mathbb{Q}}-\psi}{\sigma^2}+\frac{2\psi}{\sigma^2(1-ve^{\psi s})}, && \text{(A.18)}\\
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.19)}\\
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.20)}\\
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-ve^{\psi s}}\right)^{2\eta_j/\sigma_j^2+1}, && \text{(A.21)}\\
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-ve^{\psi s}}\right)^{2\eta_j/\sigma_j^2+2}, && \text{(A.22)}\\
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.23)}\\
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.24)}\\
\phi &= \sqrt{\left(\kappa_{i,j}^{\mathbb{Q}}\right)^2+2\sigma_{i,j}^2}, && \text{(A.25)}\\
\psi &= \sqrt{\left(\kappa_j^{\mathbb{Q}}\right)^2+2\alpha_{i,j}\sigma_j^2}, && \text{(A.26)}\\
\xi &= \sqrt{\left(\kappa^{\mathbb{Q}}\right)^2+2\gamma_{i,j}\sigma^2}, && \text{(A.27)}\\
\theta &= (\kappa_{i,j}^{\mathbb{Q}}+\phi)/(\kappa_{i,j}^{\mathbb{Q}}-\phi), && \text{(A.28)}\\
v &= (\kappa_j^{\mathbb{Q}}+\psi)/(\kappa_j^{\mathbb{Q}}-\psi), && \text{(A.29)}\\
u &= (\kappa^{\mathbb{Q}}+\xi)/(\kappa^{\mathbb{Q}}-\xi). && \text{(A.30)}
\end{aligned}
$$

References

Acharya, V., I. Dreschsler, and Schnabl, P., 2013. A Pyrrhic Victory? Bank Bailouts and Sovereign Credit Risk. *Journal of Finance*, forthcoming.

Acharya, V., L. Pedersen, T. Philippon, and Richardson, M., 2010. Measuring Systemic Risk. FRB of New York Staff Report No. 348.

Acharya, V. and Rajan, R., 2013. Sovereign Debt, Government Myopia and the Financial Sector. *Review of Financial Studies* 26, 1526-1560.

Acharya, V., I. and Schnabl, P., 2010. Do Global Banks Spread Global Imbalances? Asset-Backed Commercial Paper during the Financial Crisis of 2007-2009. *IMF Economic Review* 58, 37-73.

Acharya, V., I., and Steffen, S., 2014. The Greatest Carry Trade Ever? Understanding Eurozone Bank Risks. *Journal of Financial Economics*, forthcoming.

Adrian, T., and Brunnermeier, M., 2011. CoVaR. Working Paper.

Ang, A., and Longstaff, F., 2013. Systemic Sovereign Credit Risk: Lessons from the US and Europe. *Journal of Monetary Economics* 60, 493-510.

Angelini, P., Grande, G., and Panetta, F., 2014. The Negative Feedback Loop Between Banks and Sovereigns. *Occasional Papers* 213, Bank of Italy.

Bahansali, V., Gingrich, R., and Longstaff, F., 2008. Systemic Credit Risk: What is the Market Telling Us?. *Financial Analysts Journal* 64, 16-24.

Bank of Spain, 2011. Financial Stability Report 5/2011.

Battistini, N., Pagano, M., and Simonelli, S., 2014. Systemic Risk, Sovereign Yields and Bank Exposures in the Euro Crisis. *Economic Policy* 29, 203251.

Bauer, M., 2011. Bayesian Estimation of Dynamic Term Structure Models under Restrictions on Risk Pricing. Federal Reserve of San Francisco WP No 2011-03.

Beltratti, A., and Stultz, R. M., 2012. The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics* 105, 1-17.

Bauer, M., Rudebusch G. and Wu, J., 2012. Correcting Estimation Bias in Dynamic Term Structure Models. *Journal of Business and Economic Statistics* 30, 454-467.

Bernanke, B. S., Bertaut, C., and Kamin, S., 2011. International capital flows and the returns to safe assets in the United States, 2003-2007. in Global Imbalances and Financial Stability, Financial Stability Review, Bank of France, February.

Billio, M., Getmansky, M., Lo, A., and Pelizzon, L., 2012. Econometric Measures of Systemic Risk in the Finance and Insurance Sectors. *Journal of Financial Economics* 104, 535-559.

Bisias, D., Flood, M., Lo, A. W., and Valavanis, S., 2012. Survey of Systemic Risk Analytics. Office for Financial Research, Working Paper 1.

Black, L., Correa, R., Huang, X., and Zhou, H., 2013. The Systemic Risk of European Banks During the Financial and Sovereign Crises. Federal Reserve Board, mimeo.

Bolton, P., and Jeanne, O., 2011. Sovereign Default Risk and Bank Fragility in Financially Integrated Economies. *IMF Economic Review Volume* 59, 162-194.

Brownlees, C. T., and Engle, R., 2012. Volatility, Correlation and Tails for Systemic Risk Measurement. Working Paper, Department of Finance, NYU.

Brunnermeier, M., 2009. Deciphering the Liquidity and Credit Crunch 2007-08. *Journal of Economic Perspectives* 23, 77-100.

Cetorelli, N., and Goldberg, L. S., 2012. Banking Globalization and Monetary Transmission. *Journal of Finance* 67, 1811-43.

Cheridito, P., D. Filipovic, and Kimmel, R. L., 2007. Market Price of Risk Specifications for Affine Models: Theory and Evidence. *Journal of Financial Economics* 83, 123–170.

Committee on the Global Financial System Papers, 2011. The Impact of Sovereign Credit Risk on Bank Funding Conditions. Committee on the Global Financial System Papers No 43.

Correa, R., Lee, K-H., Sapriza, H., and Suarez, G. A., 2014. Sovereign Credit Risk, Banks' Government Support, and Bank Stock Returns around the World. *Journal of Money, Credit and Banking* 46, 93-121.

David, A. and Veronesi, P., 2014. Investor's and Central Bank's Uncertainty Embedded in Index Options. *Review of Financial Studies*, forthcoming.

Draghi, M., 2012. The Monetary Policy of the European Central Bank and its Transmission in the Euro area. Speech by the President of the ECB at Bocconi University, 15 November, 2012, Milan, Italy.

Driessen, J., 2005. Is Default Event Risk Priced in Corporate Bonds?. *Review of Financial Studies* 18, 165-195.

Duffee, G., 2002. Term Premia and Interest Rate Forecasts in Affine Models. *Journal of Finance* 57, 405-443.

Duffie, D., Pan, J., and Singleton, K., 2000. Transform Analysis and Asset Pricing for Affine Jump Diffusions. *Econometrica* 68, 1343-1376.

Duffie, D., and Singleton, K., 1999. Modeling Term Structures of Defaultable Bonds. *Review of Financial Studies* 12, 687-720.

Durbin, E., and Ng, D., 2005. The Sovereign Ceiling and Emerging Market Corporate Bond Spreads. *Journal of International Money and Finance* 24, 631-49.

EICHENGREEN, B., MODY, A., NEDELJKOVIC, M., AND SARNO, L., 2012. How the Subprime Crisis went Global: Evidence from Bank Credit Default Swap Spreads. *Journal of International Money and Finance* 31 , 1299-1318.

FELDHUTTER, P., AND NIELSEN, M.S., 2012. Systematic and Idiosyncratic Default Risk in Synthetic Credit Markets. *Journal of Financial Econometrics* 10, 292-324.

FINANCIAL TIMES, 2013a. Stop Encouraging Banks to Buy Government Debt. Financial Times, September 30, 2013.

FINANCIAL TIMES, 2013b. Naked CDS Ban Fuels Bank Funding Fears. Financial Times, April 17, 2013.

GENNAIOLI, N., MARTIN, A., AND ROSSI, S., 2013. Sovereign Default, Domestic Banks, and Financial Institutions. *Journal of Finance*, forthcoming.

GENNAIOLI, N., MARTIN, A., AND ROSSI, S., 2014. Banks, Government Bonds, and Default; What Do the Data Say? Bocconi University, mimeo.

GIGLIO, S., KELLY, B., PRUITT, S., AND QIAO, X., 2013. Systemic Risk and the Macroeconomy: An Empirical Evaluation. University of Chicago Booth School of Business, mimeo.

GONZALES-HERMOSILLO, B., AND JOHNSON, C., 2014. Transmission of Financial Stress in Europe: The Pivotal Role of Italy and Spain, but not Greece. IMF Working Paper, WP/14/76.

HANSEN, L. P., 2013. Challenges in Identifying and Measuring Systemic Risk. Working Paper University of Chicago.

HARRISON, M., AND KREPS, D., 1979. Martingales and arbitrage in multiperiod securities markets. *Journal of Economic Theory* 20, 381-408.

INTERNATIONAL MONETARY FUND, 2014. Moving from Liquidity- to Growth-Driven Markets. International Monetary Fund, Global Financial Stability Report, April 2014.

JOHANNES, M., AND POLSON, N., 2009. MCMC Methods for Financial Econometrics. In L.P. Hansen and Y. Ait-Sahalia (eds), *Handbook of Financial Econometrics*. Elsevier: Amsterdam.

KALLESTRUP, R., LANDO, D., AND MURGOCI, A., 2013. Financial Sector Linkages and the Dynamics of Bank and Sovereign Credit Spreads. Working Paper, Copenhagen Business School.

KASHYAP, A., AND STEIN, J., 2000. What Do A Million Observations on Banks Say About the Transmission of Monetary Policy?. *American Economic Review* 90, no. June: 407-428.

KASHYAP, A., AND STEIN, J., 2004. Cyclical implications of the Basel II capital standards. *Economic Perspectives* 28, 18-31.

KELLY, B., PASTOR, L., AND VERONESI, P., 2014. The Price of Political Uncertainty: Theory and Evidence from the Option Market. The University of Chicago Booth School of Business, mimeo.

Korte, J. and Steffen, S., 2014. Zero Risk Contagion - Banks' Sovereign Exposure and Sovereign Risk Spillovers. Goethe University Frankfurt, mimeo.

Laeven, L., Ratnovski, L., and Tong, H., 2014. Bank Size and Systemic Risk. IMF Staff Discussion Note, SDN/14/04.

Lamont, B., Correa, R., Huang, X., and Zhou, H., 2013. The Systemic Risk of European Banks during the Financial and Sovereign Debt Crises. Federal Reserve Board, mimeo.

Li, J., and Zinna, G., 2014. On Bank Credit Risk: Systemic or Bank-specific? Evidence from the US and UK. *Journal of Financial and Quantitative Analysis* 49, 1403–1442.

Lindner, F., 2013. Banken treiben Eurokrise (Banks drive the Euro crisis), IMK Report 82, June.

Longstaff, F. A., Mithal, S., Neis, E., 2005. Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *Journal of Finance* 60, 2213-2253.

Longstaff, F., Pan, J., Pedersen, L., and Singleton, K., 2011. How Sovereign is Sovereign Credit Risk?. *American Economic Journal: Macroeconomics* 3, 75-103.

Longstaff, F. and Rajan, A., 2008. An Empirical Analysis of the Pricing of Collateralized Debt Obligations. *Journal of Finance* 63, 509-563.

Mayordomo, S., Pena, J.I. and Schwartz, E.S., 2010. Are all Credit Default Swap Databases Equal?. NBER Working Paper No. 16590.

Mersch, Y., 2013. Built to Last: The New Euro Area Framework. Speech by the Member of the Executive Board of the ECB, Barclays Research Conference, London, May 17, 2013.

Neal, R. M., 2003. Slice sampling (with discussions). *Annals of Statistics* 31, 705-767.

Noeth, B., and Sengupta, R., 2012. Global European Banks and the Financial Crisis. Federal Reserve Bank of St. Louis Review, November/December.

Noss, J., and Sowerbutts, R., 2012. The Implicit Subsidy of Banks. Bank of England, Financial Stability Report 15, May 2012.

Pagano, M. S., and Sedunov, J., 2014. What Is the Relation Between Systemic Risk Exposure and Sovereign Debt? Villanova University, mimeo.

Pan, J., and Singleton, K., 2008. Default and Recovery Implicit in the Term Structure of Sovereign CDS spreads. *Journal of Finance* 63, 2345-2384.

Panetta F., Faeh, T., Grande, G., Ho, C., King, M., Levy, A., Signoretti, F., Taboga, M., and Zaghini, A., 2009. An Assessment of Financial Sector Rescue Programmes. BIS Papers No 48 (July).

Pastor, L., and Veronesi, P., 2012. Uncertainty about Government Policy and Stock Prices. *Journal of Finance* 64, 1219-1264.

Pastor, L., and Veronesi, P., 2013. Political Uncertainty and Risk Premia. *Journal of Financial Economics* 110, 520-545.

Reinhart, C. M., and Rogoff, K. S., 2009. *This Time is Different: Eight Centuries of Financial Folly.* Princeton University Press.

Siriwardane, E. N., 2015. Concentrated Capital Losses and the Pricing of Corporate Credit Risk. NYU Stern School of Business, mimeo.

Stein, J., 2014. Incorporating Financial Stability Considerations into a Monetary Policy Framework. International Research Forum on Monetary Policy, Washington, D.C., USA.

Tsesmelidakis, Z., and Merton, R. C., 2012. The Value of Implicit Guarantees. International Monetary Fund, Working Paper 128.

Van Rompuy, H., Barroso, J. M., Juncker, J. C., and Draghi, M., 2012. Towards a Genuine Economic and Monetary Union. The Four Presidents' Report, December 5, 2012.

Weidmann, J., 2013. Stop Encouraging Banks to Buy Government Debt. Financial Times, September 30, 2013.

Xu, S., In, F., Forbes, C., and Hwang, I., 2014. Systemic Risk in the European Sovereign and Banking System, Monash University, mimeo.

Zinna, G., 2013. Sovereign default risk premia: Evidence from the default swap market. *Journal of Empirical Finance* 21, 15-35.

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 Espaniol 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 of 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: **Systematic and Country Intensities' Parameter Estimates**

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

Table 3: **Systematic 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 systematic ($\alpha_{i,j}$) and country ($\gamma_{i,j}$) sovereign exposures, as well as the summary statistics of the systematic ($SIW = \alpha_{i,j}S_t/(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$) 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 systematic and country intensity weights are displayed in percentages.

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

	(1)	(2)	(3)	(4)	(5)
			Panel A: SIW+CIW		
Size	0.457***			0.346*	0.416***
(se)	(0.0816)			(0.170)	(0.123)
SExp		6.926***		2.432	
(se)		(1.724)		(3.453)	
SSub			25.35***		4.194
(se)			(8.623)		(10.13)
Con.	22.73***	20.47***	23.65***	20.63***	21.99***
(se)	(3.129)	(4.079)	(4.134)	(4.211)	(3.773)
# Obs.	21	21	21	21	21
R^2	0.528	0.427	0.318	0.550	0.533
			Panel B: SIW		
	(1)	(2)	(3)	(4)	(5)
Size	0.179**			0.109	0.116
(se)	(0.0646)			(0.0769)	(0.0734)
FSExp		4.089***		2.311	
(se)		(1.405)		(1.908)	
FSSub			15.40**		8.273
(se)			(5.936)		(8.074)
Con.	14.11***	16.08***	15.83***	14.39***	14.17***
(se)	(1.930)	(1.854)	(1.857)	(1.935)	(1.931)
# Obs.	21	21	21	21	21
R^2	0.195	0.189	0.180	0.226	0.222
			Panel C: CIW		
	(1)	(2)	(3)	(4)	(5)
Size	0.278***			0.198***	0.210***
(se)	(0.0696)			(0.0601)	(0.0472)
DSExp		6.942***		5.178**	
(se)		(1.757)		(1.907)	
DSSub			36.99***		30.03***
(se)			(7.441)		(6.628)
Con.	8.621***	6.308**	6.939**	3.505	3.074
(se)	(2.465)	(2.813)	(2.689)	(3.118)	(3.172)
# Obs.	21	21	21	21	21
R^2	0.367	0.397	0.446	0.558	0.639

This table reports the cross-sectional regressions of the bank mean sovereign intensity weights (SIW+CIW) and its systematic (SIW) and country (CIW) components on several standard measures of banks' exposures to sovereign risk. *Panel A* reports the regressions of SIW+CIW on bank size, individual bank holdings of sovereign securities (SExp), and sovereign subsidies (SSub). *Panel B* (*Panel C*) reports the regressions of SIW (CIW) on bank size, individual bank holdings of domestic (DSExp) and non-domestic (FSExp) sovereign securities, and of domestic (DSSub) and non-domestic (FSSub) sovereign subsidies. The holdings of sovereign securities were published by the EBA as a result of the 2011 stress tests and the sovereign subsidy is constructed as in Korte and Steffen (2014) by assigning appropriate risk weights to each holding of sovereign debt. All regressors are standardized by the domestic GDP. (***), (**), and (*) denote the 1-, 5-, and 10-percent levels of significance, respectively, where White (1980) heteroskedastic-consistent standard errors (se) are used. Sources: Capital IQ and European Banking Authority.

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

	Panel A: $\gamma_{i,j}$			
	(1)	(2)	(3)	(4)
All-in-all CR	0.215*			
(se)	(0.116)			
Stand-alone CR		-0.0227		0.172
(se)		(0.0818)		(0.102)
Uplift			0.203**	0.339**
(se)			(0.0930)	(0.149)
Size				
(se)				
Constant	-0.719	1.337**	0.767***	-0.680
(se)	(1.069)	(0.594)	(0.225)	(0.978)
# Obs.	20	20	20	20
R^2	0.145	0.003	0.162	0.249

	Panel B: CIW			
	(1)	(2)	(3)	(4)
All-in-all CR	2.243			
(se)	(1.378)			
Stand-alone CR		4.615***		3.626**
(se)		(0.970)		(1.492)
Uplift			-4.604***	-1.724
(se)			(1.584)	(2.099)
Size				
(se)				
Constant	-3.290	-14.80**	25.99***	-4.551
(se)	(12.24)	(6.347)	(4.909)	(14.39)
# Obs.	20	20	20	20
R^2	0.066	0.488	0.351	0.515

This table reports the cross-sectional regressions of banks' exposures to country risk ($\gamma_{i,j}$) in the top panel, and of the mean country intensity weight, $CIW = \gamma_{i,j}C_{t,i}/(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$, in the lower 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). ***, **, and * denote the 1-, 5-, and 10-percent levels of significance, respectively, where White (1980) heteroskedastic-consistent standard errors (se) are used. Source: Bloomberg.

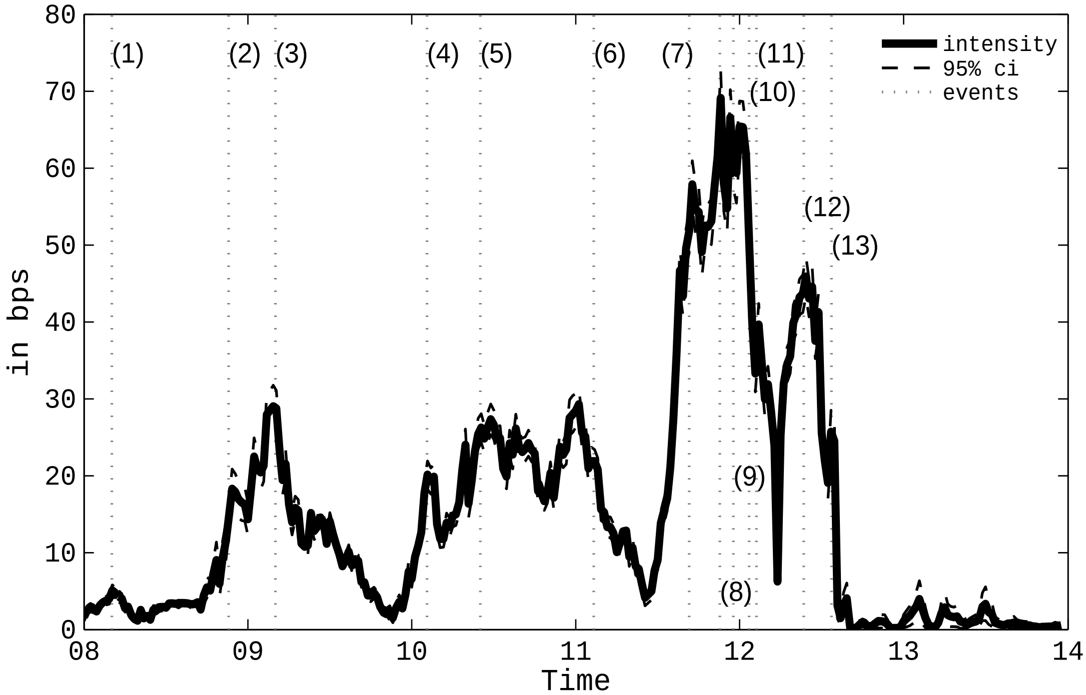

Figure 1: **Sovereign Euro Area Tail Risk**

This figure plots the time series of the estimated joint-sovereign default intensity (S_t) and its 95% credible interval. The intensity process is measured in basis points. Dotted vertical 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 spiraling 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).

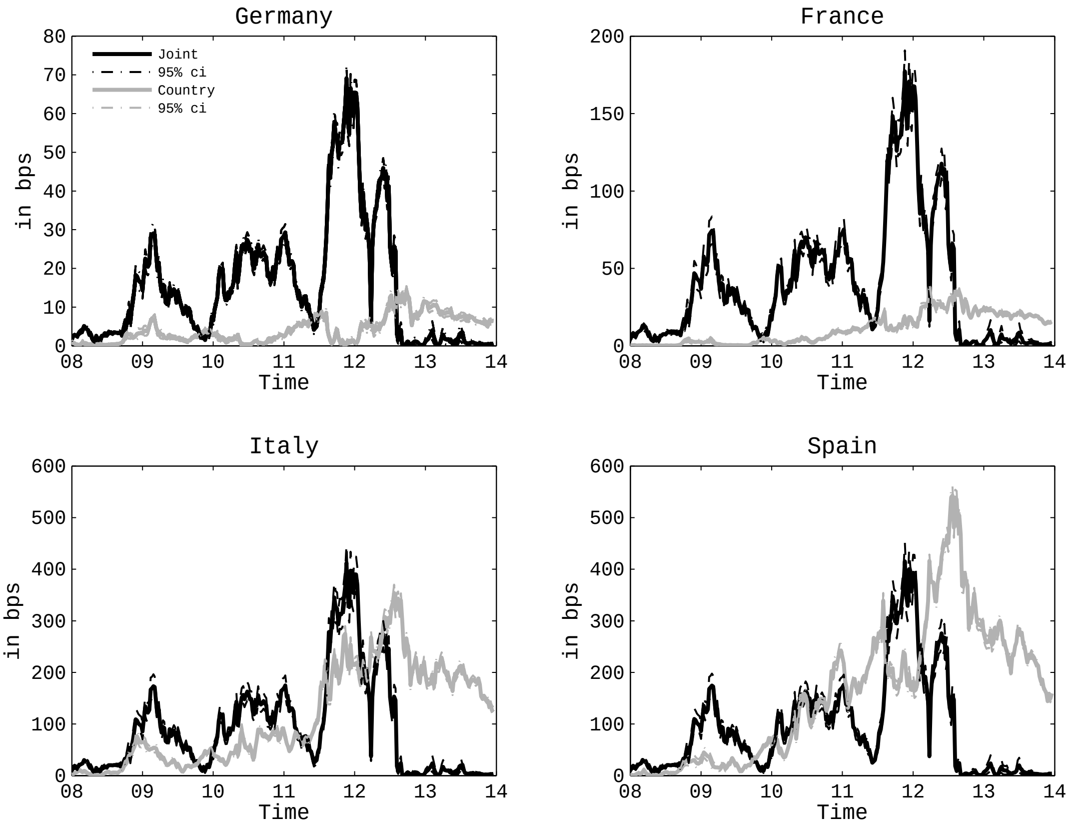

Figure 2: **Systemic and Country Sovereign Credit Risk**

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

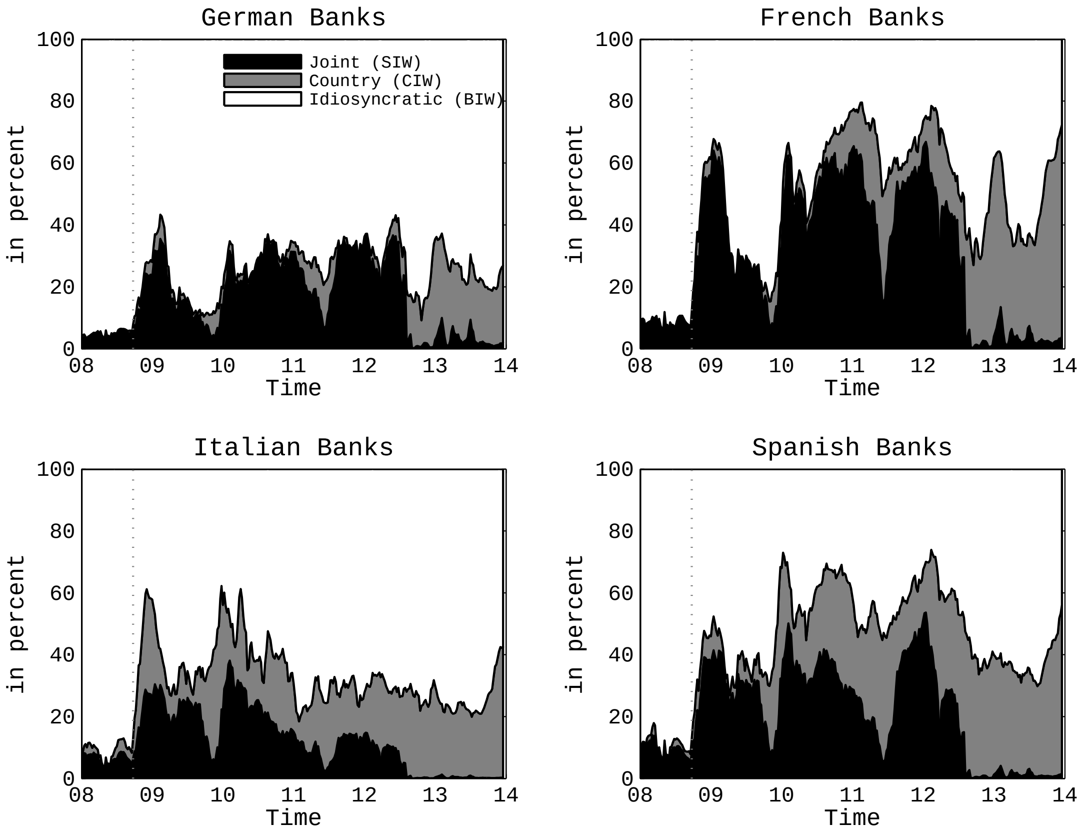

Figure 3: **Bank Systemic, Country, and Idiosyncratic Intensity Weights**

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.

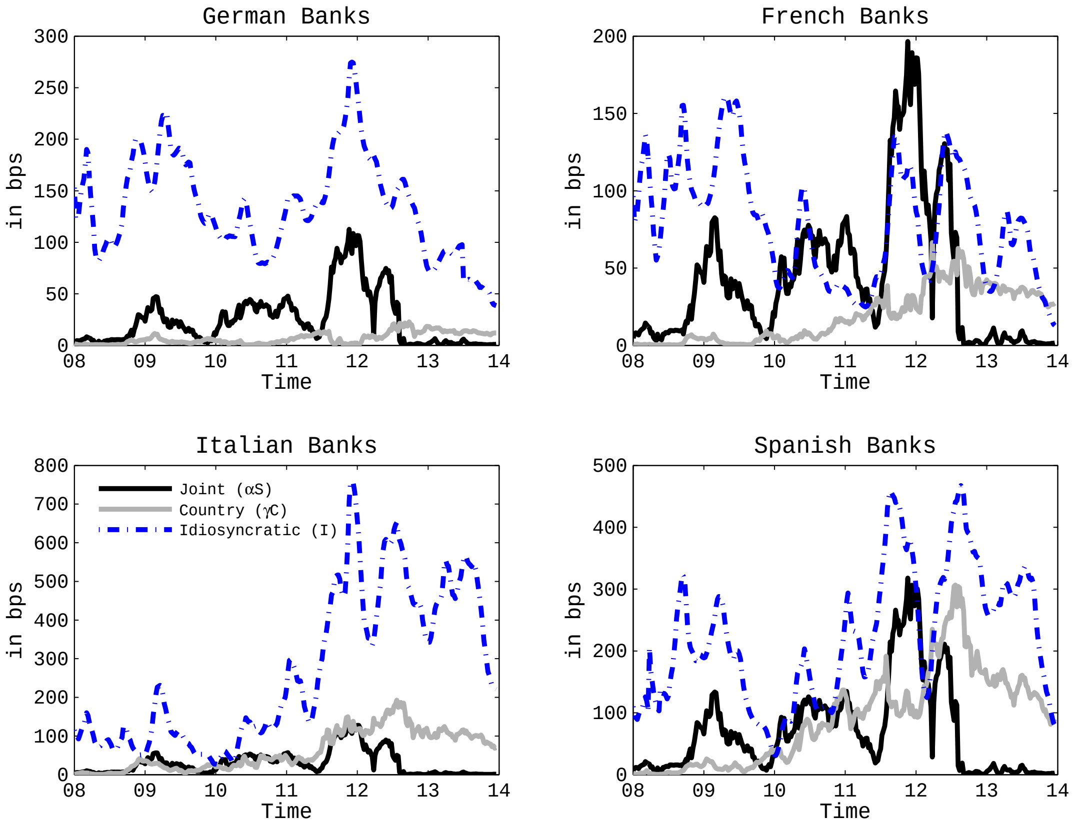

Figure 4: **Average Bank Systematic, Country, and Idiosyncratic Intensities**

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

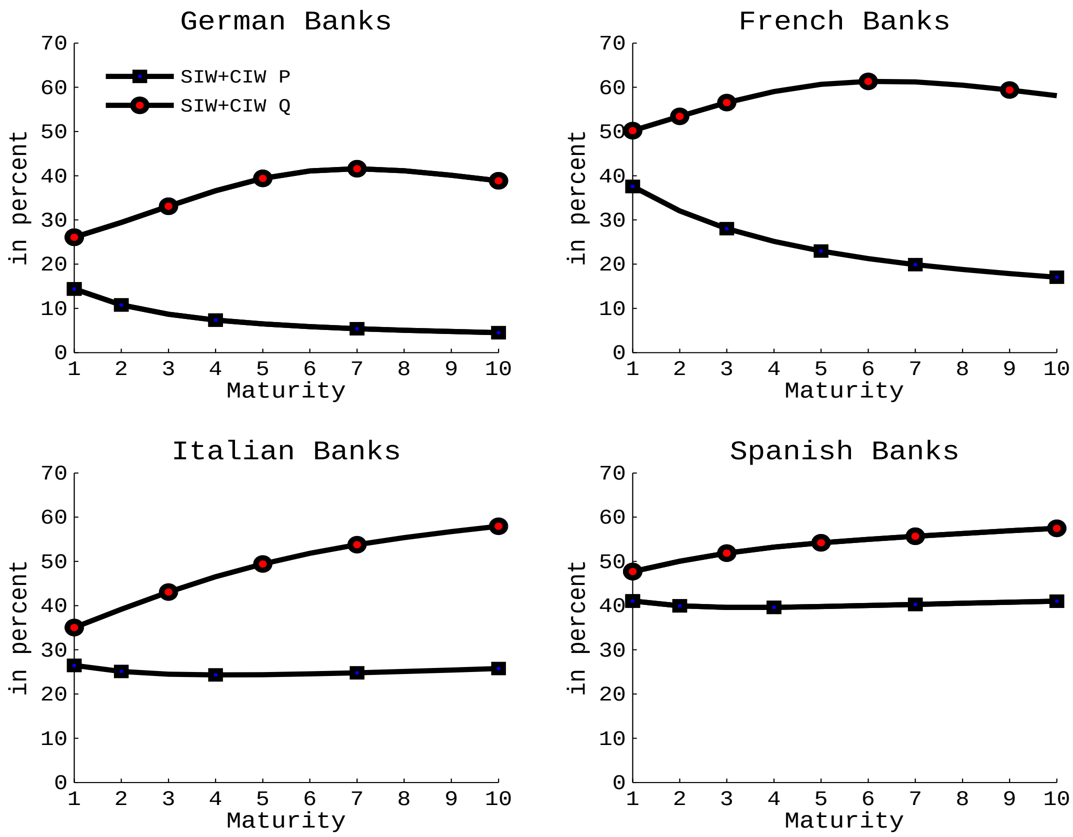

Figure 5: **Decomposing Bank CDS: Term Structures and Distress Risk Premia**

This figure presents: (1) the fraction of bank credit risk that is due to sovereign risk at different horizons, i.e., $SIW^{\mathbb{P}}(M) + CIW^{\mathbb{P}}(M)$ where M denotes the maturity, and (2) the fraction of bank CDSs that is due to sovereign credit risk which therefore also include the effect of the distress risk premia, i.e., $SIW^{\mathbb{Q}}(M) + CIW^{\mathbb{Q}}(M)$. Results are presented by country groups.

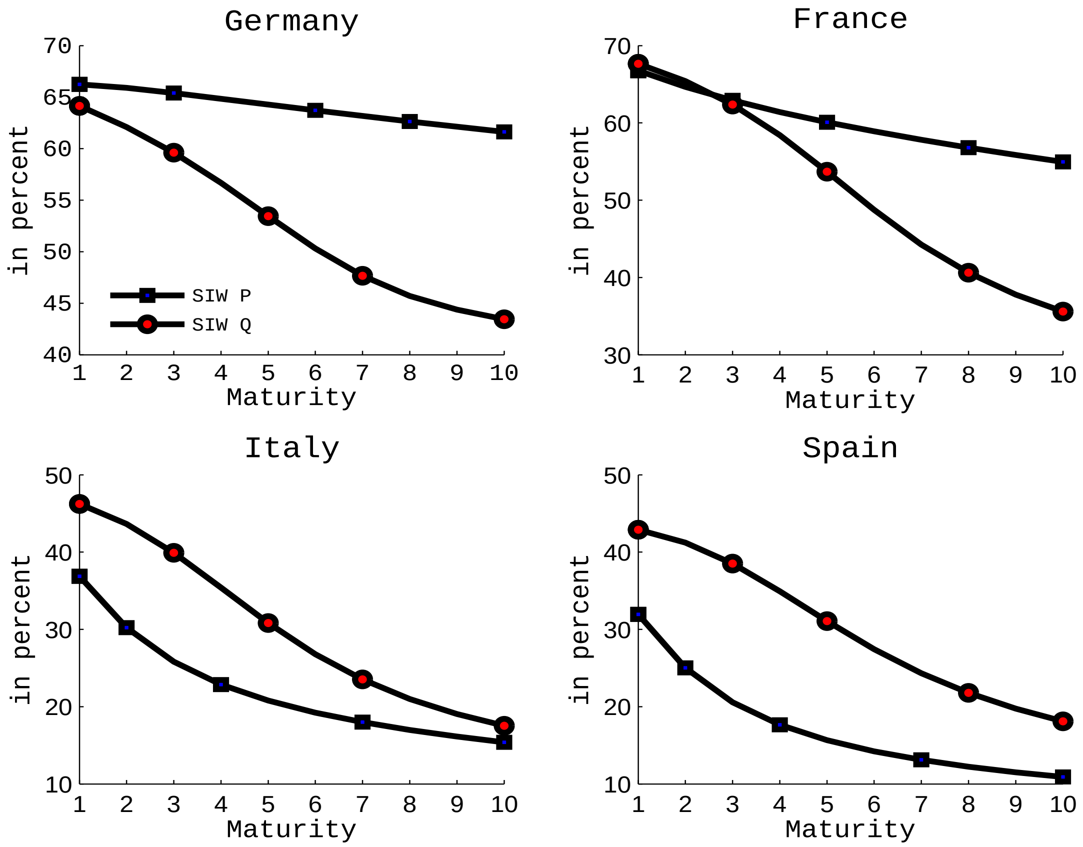

Figure 6: **Decomposing Sovereign CDS: Term Structures and Distress Risk Premia**

This figure presents: (1) the fraction of sovereign credit risk that is due to Euro area tail risk at different horizons, i.e., $SIW^{\mathbb{P}}(M)$, where M denotes the maturity, and (2) the fraction of the sovereign CDSs that is due to Euro area tail risk, which therefore also accounts for the effect of the distress risk premia, i.e., $SIW^{\mathbb{Q}}(M)$.

Internet Appendix

(not for publication)

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

by

Junye Li and Gabriele Zinna

I Bayesian Estimation

A number of factors make Bayesian methods widely used, see, *e.g.*, Bauer (2011), in the estimation of term structure models of interest rates: the likelihood function is generally high dimensional and strongly non-linear in the model parameters, and is characterized by multiple local maxima; the dynamics of the underlying factors driving the bond pricing are generally highly persistent and the estimation sample is relatively small, leading to a small-sample bias issue (Bauer, Rudebush and Wu, 2012); post-estimation calculations, such as impulse response functions and bond risk premia, are based on highly non-linear functions of the estimated parameters. All of this can be easily dealt with in a Bayesian setting, whereas it is not straightforward in a frequentist setting. 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. For this reason, in order to draw the intensities, we implement a single-move algorithm which does not require assumptions such as normality and linearity. Indeed our MCMC algorithm delivers exact finite sample properties of the estimates.

I.1 State-Space Representations

Stage 1: Sovereign credit risk. The discretized transition equations, based on the standard Euler scheme applied to a small time interval τ, take the form of:

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

where b_t and $w_{t,i}$ are mutually independent standard normal noises. Thus, there are five transition equations: the joint-sovereign intensity and four 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 $\text{CDS}_{t,i}^{obs}$. Thus, the observation space for sovereign i at time t is given by:

$$\text{CDS}_{t,i}^{obs} = f\left(S_t, C_{t,i}, \theta^{\mathbb{Q}}, \theta_i^{\mathbb{Q}}, \alpha_i\right) + \epsilon_{t,i}, \qquad \epsilon_{t,i} \sim N\left(0, \Sigma_{t,i}\right), \tag{I.3}$$

where $f(\cdot)$ is the two-factor CDS pricing function, which depends on the joint and country-specific 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).[34]

The CDS contract of maturity M of sovereign i is assumed to be priced with normally

[34] 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 (2014). To economize on space, we refer the reader to those studies.

distributed errors with a mean of zero and a standard deviation of $\sigma_{\epsilon,i}\left|Bid_{t,i}(M) - Ask_{t,i}\left(M\right)\right|$. 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. 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.

Stage 2: Bank credit risk. 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:

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

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 $\sigma_{\epsilon,i,j}\left|Bid_{t,i,j}(M) - Ask_{t,i,j}\left(M\right)\right|$. Finally, the additional transition equation is:

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

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

I.2 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:

$$p(\Theta, X|D) \propto p(D|X, \Theta)p(X|\Theta)p(\Theta), \tag{I.6}$$

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 (2014). There are, however, two differences worth mentioning. First, Li and Zinna (2014) 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.

In the second-stage we estimate separately for each bank (i, j) its latent intensity $I_{t,i,j}$; the associated risk-neutral parameters $\theta_{i,j}^{\mathbb{Q}} = [\eta_{i,j}, \kappa_{i,j}^{\mathbb{Q}}, \sigma_{i,j}]$; the objective mean reversion $\kappa_{i,j}^{\mathbb{P}}$; 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.

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. 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.

I.3 Detailed 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 intensities, and to quantify the uncertainty around the estimates. In the following, we describe the MCMC algorithm in detail. Note that we use flat priors.

I.4 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 (2014). The model takes the following state-space form:

Measurement Equations:

$$CDS_{t,i}^{obs} = f(S_t, C_t, \theta^{\mathbb{Q}}, \theta_i^{\mathbb{Q}}, \alpha_i) + \epsilon_{t,i}, , \qquad \epsilon_{t,i} \sim N\left(0, \Sigma_{t,i}\right), \tag{I.7}$$

State Equations:

$$\begin{aligned} S_t &= \eta\tau + (1 - \kappa^{\mathbb{P}}\tau)S_{t-\tau} + \sigma\sqrt{\tau S_{t-\tau}}b_t, & \text{(I.8)} \\ C_{t,i} &= \eta_i\tau + (1 - \kappa_i^{\mathbb{P}}\tau)C_{t-\tau,i} + \sigma_i\sqrt{\tau C_{t-\tau,i}}w_{t,i}, & \text{(I.9)} \end{aligned}$$

As the MCMC algorithm closely follows Li and Zinna (2014), 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 (2014). 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.5 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:

$$CDS_{t,i,j}^{obs} = s\left(S_t, C_{t,i}, I_{t,i,j}, \theta^{\mathbb{Q}}, \theta_i^{\mathbb{Q}}, \theta_{i,j}^{\mathbb{Q}}, \alpha_{i,j}, \gamma_{i,j}\right) + \epsilon_{t,i,j}, \qquad \epsilon_{t,i,j} \sim N\left(0, \Sigma_{t,i,j}\right), \tag{I.10}$$

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

$$I_{t,i,j} = \eta_{i,j}\tau + (1 - \kappa_{i,j}^{\mathbb{P}}\tau)I_{t-\tau,i,j} + \sigma_{i,j}\sqrt{\tau I_{t-\tau,i,j}}z_{t,i,j}. \tag{I.11}$$

Similar to the first-stage estimation, $\kappa_{i,j}^{\mathbb{P}}$ 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 (2014). 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 ($\kappa_{i,j}^{\mathbb{P}}$). The parameters $\kappa_{i,j}^{\mathbb{P}}$ only enter the objective dynamics. Therefore, it follows that:

$$\begin{aligned} p(\kappa_{i,j}^{\mathbb{P}}|CDS_{1:T,i,j}^{obs}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-) &\propto p(I_{1:T,i,j}|\kappa_{i,j}^{\mathbb{P}}, \Theta_-)p(\kappa_{i,j}^{\mathbb{P}}) \\ &\propto \exp\left(-\frac{1}{2}\sum_{t=1}^{T}\frac{(I_{t,i,j}-\eta_{i,j}\tau-(1-\kappa_{i,j}^{\mathbb{P}}\tau)I_{t-1,i,j})^2}{\sigma_{i,j}^2\tau I_{t-1,i,j}}\right)p(\kappa_{i,j}^{\mathbb{P}}) \\ &\propto \exp\left(-\frac{1}{2}\sum_{t=1}^{T}\frac{(a_t\kappa_{i,j}^{\mathbb{P}}-b_t)^2}{\sigma_{i,j}^2\tau I_{t-1,i,j}}\right)p(\kappa_{i,j}^{\mathbb{P}}), \end{aligned} \tag{I.12}$$

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 distribution is a normal $\kappa_{i,j}^{\mathbb{P}} \to N(Qm, \mathbb{Q})$, where $m = \sum_{t=1}^{T}\frac{a_t b_t}{\sigma_{i,j}^2\tau I_{t-1,i,j}}$ and $\mathbb{Q}^{-1} = \sum_{t=1}^{T}\frac{a_t^2}{\sigma_{i,j}^2\tau I_{t-1,i,j}}$.

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

$$\begin{aligned} &p(\sigma_{\epsilon,i,j}^2|CDS_{1:T,i,j}^{obs}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-) \\ &\propto p(CDS_{1:T,i,j}^{obs}|\sigma_{\epsilon,i,j}^2, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-)p(\sigma_{\epsilon,i,j}^2) \\ &\propto \sigma_{\epsilon,i,j}^{-TM}\exp\left[-\frac{1}{2}\sum_{t=1}^{T}\sigma_{\epsilon,i,j}^{-2}\hat{e}_{t,i,j}'\hat{e}_{t,i,j}\right]p(\sigma_{\epsilon,i,j}^2), \end{aligned} \tag{I.13}$$

where $\hat{e}_{t,i,j}$ is the pricing error $[CDS_{t,i,j}^{obs} - s(\cdot)]BA_t^{-1}$. Thus, $\sigma_{\epsilon,i,j}^{-2}$ 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:

$$\begin{aligned} &p(\eta_{i,j}, \sigma_{i,j}|CDS_{1:T,i,j}^{obs}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_-) \\ &\propto \prod_{t=1}^{T}p(CDS_{t,i,j}^{obs}|S_t, C_{t,i}, I_{t,i,j}, \Theta)p(I_{t,i,j}|I_{t-1,i,j}, \eta_{i,j}, \sigma_{i,j})p(\eta_{i,j}, \sigma_{i,j}) \\ &\propto \frac{1}{\sigma_{i,j}^T}\exp\left[-\frac{1}{2}\sum_{t=1}^{T}\left(\sigma_{\epsilon,i,j}^{-2}\hat{e}_{t,i,j}'\hat{e}_{t,i,j} + \frac{A_t}{\sigma_{i,j}^2\tau I_{t-1,i,j}}\right)\right]p(\eta_{i,j}, \sigma_{i,j}), \end{aligned} \tag{I.14}$$

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

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

$$\begin{aligned}
&p(\kappa^{\mathbb{Q}}_{i,j}, \gamma_{i,j} | CDS^{obs}_{1:T,i,j}, S_{1:T}, C_{1:T,i}, I_{1:T,i,j}, \Theta_{-}) \\
&\propto \prod_{t=1}^{T} p(CDS^{obs}_{t,i,j} | S_t, C_{t,i}, I_{t,i,j}, \Theta) p(\kappa^{\mathbb{Q}}_{i,j}, \gamma_{i,j}) \\
&\propto \exp\left[-\frac{1}{2}\sum_{t=1}^{T} \sigma^{-2}_{\epsilon,i,j} \hat{e}'_{t,i,j} \hat{e}_{t,i,j}\right] p(\kappa^{\mathbb{Q}}_{i,j}, \gamma_{i,j}).
\end{aligned} \tag{I.15}$$

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:

$$\begin{aligned}
&p(I_{t,i,j} | CDS^{obs}_{1:T,i,j}, S_{1:T}, C_{1:T,i}, I_{-t,i,j}\Theta) \\
&\propto p(CDS^{obs}_{t,i,j} | S_t, C_{t,i}, I_{t,i,j}, \Theta) p(I_{t,i,j} | I_{t+1,i,j}, I_{t-1,i,j}, \Theta) \\
&\propto p(CDS^{obs}_{t,i,j} | S_t, C_{t,i}, I_{t,i,j}, \Theta) p(I_{t+1,i,j} | I_{t,i,j}, \Theta) p(I_{t,i,j} | I_{t-1,i,j}, \Theta),
\end{aligned} \tag{I.16}$$

where the first term in (I.16) is:

$$p(CDS^{obs}_{t,i,j} | \cdot) \quad \propto \quad \exp\left[-\frac{1}{2}\sigma^{-2}_{\epsilon,i,j} \hat{e}'_{t,i,j} \hat{e}_{t,i,j}\right], \tag{I.17}$$

and the second and third terms are given by:

$$p(I_{t+1,i,j} | \cdot) \quad \propto \quad \frac{1}{\sigma_{i,j}\sqrt{\tau I_{t,i,j}}} \exp\left(-\frac{1}{2}\frac{(I_{t+1,i,j} - \eta_{i,j}\tau - (1-\kappa^{\mathbb{P}}_{i,j}\tau) I_{t,i,j})^2}{\sigma^2_{i,j}\tau I_{t,i,j}}\right), \tag{I.18}$$

$$p(I_{t,i,j} | \cdot) \quad \propto \quad \exp\left(-\frac{1}{2}\frac{(I_{t,i,j} - \eta_{i,j}\tau - (1-\kappa^{\mathbb{P}}_{i,j}\tau) I_{t-1,i,j})^2}{\sigma^2_{i,j}\tau I_{t-1,i,j}}\right). \tag{I.19}$$

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

$$p(I_{T,i,j} | \cdot) \propto p(CDS^{obs}_{T,i,j} | S_T, C_{T,i}, I_{T,i,j}, \Theta) p(I_{T,i,j} | I_{T-1,i,j}, \Theta), \tag{I.20}$$

and at time $t = 1$ it becomes:

$$p(I_{1,i,j} | \cdot) \propto p(CDS^{obs}_{1,i,j} | S_1, C_{1,i}, I_{1,i,j}, \Theta) p(I_{2,i,j} | I_{1,i,j}, \Theta). \tag{I.21}$$

II 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.

II.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).[35] 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 spread priced under the risk-neutral probability measure (CDS) and under the objective measure ($\mathrm{CDS}^{\mathbb{P}}$). The pricing of both CDS and $\mathrm{CDS}^{\mathbb{P}}$ 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 $\mathrm{CDS}^{\mathbb{P}}$ 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.[36] Take, for example, the systemic risk premium, which consists of replacing $\kappa^{\mathbb{Q}}$ with $\kappa^{\mathbb{P}}$ when pricing the CDS contract. We

[35] 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.

[36] 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.

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.

II.2 Empirical Estimates

Table A5 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 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 A6 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.

III Additional Tables

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

	CDS Spreads					BID-ASK Spreads				
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. All numbers are reported in basis points. Source CDS data: CMA.

Table A2: **Pricing Errors**

	MAPE (in bps)					MAPPE (in %)				
	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 in basis point, MAPE, and the mean absolute percentage pricing errors in percent, MAPPE, for the CDS with the indicated maturities. The results are grouped by country. The estimates result from implementing the Bayesian algorithm, described in Section 3, on weekly CDS data from January 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							
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							
	$\eta_{i,j}$	$\kappa^{\mathbb{P}}_{i,j}$	$\sigma_{i,j}$	$k^{\mathbb{Q}}_{i,j}$	$\alpha_{i,j}$	$\gamma_{i,j}$	$\sigma^{i,j}_{\epsilon}$
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							
	$\eta_{i,j}$	$\kappa^{\mathbb{P}}_{i,j}$	$\sigma_{i,j}$	$k^{\mathbb{Q}}_{i,j}$	$\alpha_{i,j}$	$\gamma_{i,j}$	$\sigma^{i,j}_{\epsilon}$
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						
	$\eta_{i,j}$	$\kappa^{\mathbb{P}}_{i,j}$	$\sigma_{i,j}$	$k^{\mathbb{Q}}_{i,j}$	$\alpha_{i,j}$	$\gamma_{i,j}$	$\sigma^{i,j}_{\epsilon}$
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 estimates result from implementing the Bayesian algorithm, described in Section 3, on weekly CDS data from January 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 ($\mathrm{I}_{t,i,j}$). 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. The $\mathrm{I}_{t,i,j}$ estimates result from implementing the Bayesian algorithm, described in Section 3, on weekly CDS data from January 2008 to December 18, 2013.

Table A5: **Term Structure of Sovereign Risk Premia Components**

Panel A: Germany

	Total				Systematic				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				Systematic				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				Systematic				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				Systematic				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 systematic sovereign default intensity ($\alpha_i S_t$); and the right panels denote the risk premia induced by the country default intensity ($C_{t,i}$).

Table A6: **Term Structure of Bank Risk Premia Components by Country Averages**

Panel A: German Banks

	Total				Systematic				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				Systematic				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				Systematic				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				Systematic				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 ($\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j}$); *Systematic* 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 ($I_{t,i,j}$).

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

	3-year Mean	SDev	Min	Max	5-year Mean	SDev	Min	Max	10-year Mean	SDev	Min	Max
Total Risk Premia												
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
Systematic Risk Premia												
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												
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												
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 ($\alpha_{i,j}S_t+\gamma_{i,j}C_{t,i}+I_{t,i,j}$); *Systematic* denotes the risk premia induced by the scaled systematic sovereign 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: France**

	3-year				5-year				10-year			
Total Risk Premia												
	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
Systematic Risk Premia												
	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												
	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												
	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 $(\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j})$; *Systematic* denotes the risk premia induced by the scaled systematic sovereign 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 A9: **Term Structure of Individual Bank Risk Premia Components: Italy**

	3-year				5-year				10-year			
Total Risk Premia	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
Systematic Risk Premia	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	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	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 ($\alpha_{i,j}S_t + \gamma_{i,j}C_{t,i} + I_{t,i,j}$); *Systematic* denotes the risk premia induced by the scaled systematic sovereign 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 A10: **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
	Systematic 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 ($\alpha_{i,j}S_t+\gamma_{i,j}C_{t,i}+I_{t,i,j}$); *Systematic* denotes the risk premia induced by the scaled systematic sovereign 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 ($I_{t,i,j}$).

IV Additional Figures

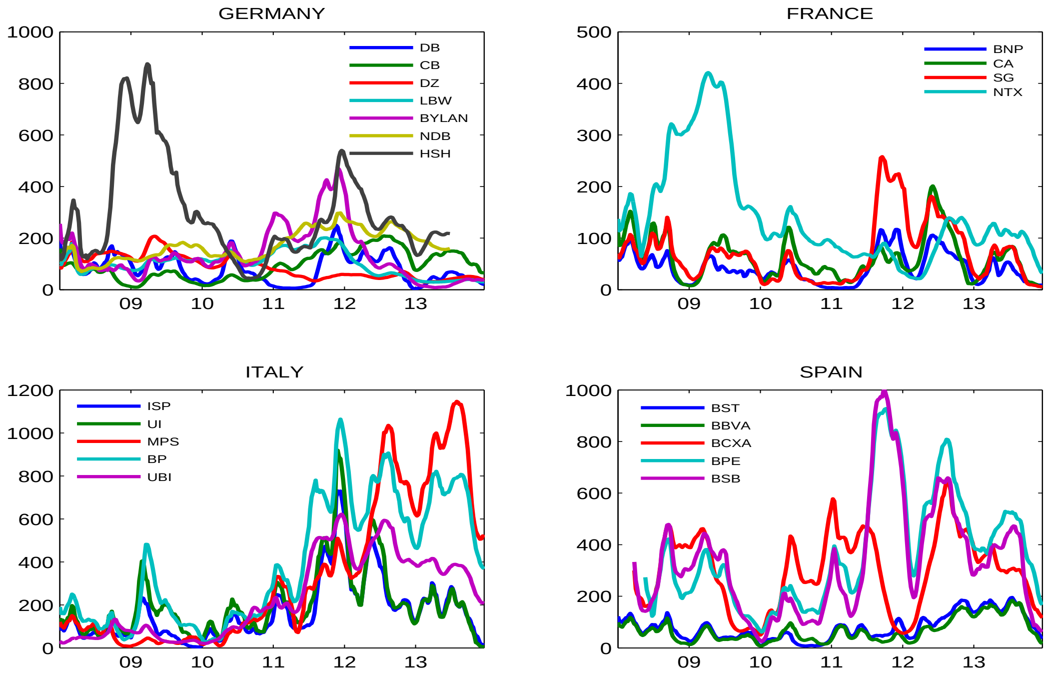

Figure A.1: **Idiosyncratic Intensities by Country**

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

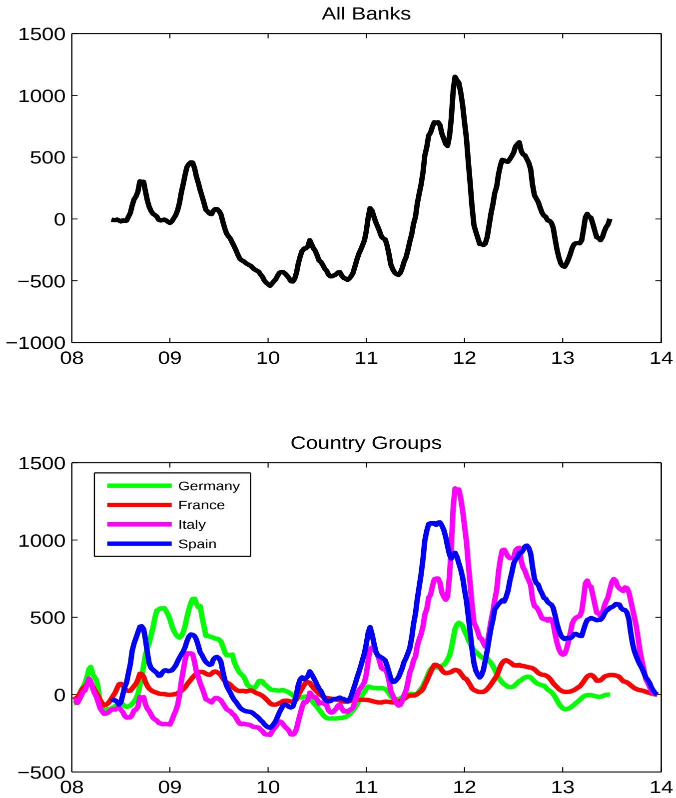

Figure A.2: **Principal Component Analysis of Bank Idiosyncratic Intensities**

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.

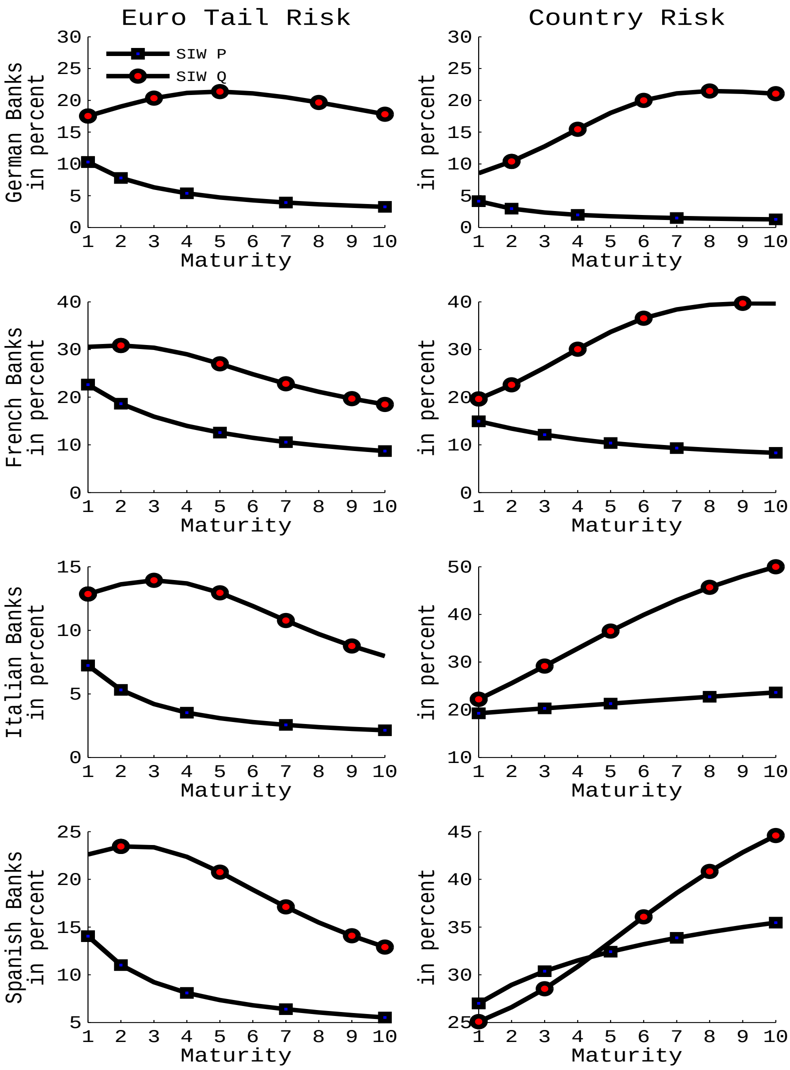

Figure A.3: **Decomposing Bank CDS**

This figure presents: 1) the fraction of bank credit risk which is due to Euro area tail risk and country risk at different horizons, i.e. $SIW^{\mathbb{P}}(M)$ and $CIW^{\mathbb{P}}(M)$, respectively, where M denotes the maturity; and, 2) the fraction of bank CDSs which is due to Euro area tail risk and country risk which therefore also include the effect of the distress risk premia, i.e. $SIW^{\mathbb{Q}}(M)+CIW^{\mathbb{Q}}(M)$. Results are presented by country groups.