

Credit risk “Beta”: the systematic aspect of bank default risk

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Abstract

Using information in US and European bank and sovereign Credit Default Swap (CDS) spreads we study the systematic component of banks’ credit risk that stems from their common exposure to sovereign default risk. Based on a default intensity model, we propose a measure of the “multiplier” of risk transmission from a sovereign to a local bank—credit risk Beta (c-Beta). During our sample period 2008-2014, on average US banks are much less sensitive to sovereign risk than their European counterparts. Across countries within Europe, the systematic component accounts for quite different proportions of the total bank default risk. We also empirically confirm the asset holdings channel of the risk contagion theory by showing that a bank’s c-Beta estimated with our model is positively related to its holdings of sovereign debt. Our findings have policy implications with respect to financial stability.

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1. Introduction

The European debt crisis has shown that bank default risk and sovereign default risk are closely interconnected. The relationship between the financial health of the banking sector and the fiscal situation of the government is bidirectional and mutually reinforcing. On the one hand, a banking crisis may lead to distressed public finances because the government explicitly and implicitly guarantees the private debt of systemically important financial firms. On the other hand, increased sovereign risk can weaken local banks' credit strength, which is what we intend to investigate with this paper. Sovereign debt was once regarded as the most liquid and safest asset before the recent financial crises, especially for developed countries such as the United States and the European countries analysed in the paper. However, the recent sovereign debt crisis has demonstrated that government debt can become rather risky for a variety of reasons, among which bank bailouts are shown to be an important cause by Acharya et al. (2014). There are several channels of risk transmission from a sovereign to local banks. The most obvious and intuitive one is the fact that sovereign credit strength is perceived as the ceiling of corporate (including banks) credit strength, described as the "sovereign ceiling" in Reinhart and Rogoff (2011). The increase of sovereign default risk puts upward pressure on the credit spread of banks in the country. One recent example is that following the downgrade of Spanish sovereign bonds on 13 June 2012, Moody's downgrades 28 Spanish banks by one to four notches (see Moody's Investors Service, 2012a and 2012b). Another mechanism works through weakened economic growth (macro-economic fundamentals) resulting from deteriorated sovereign credit strength, which is beyond the scope of our paper. In addition, bank credit risk is directly linked to sovereign risk through the substantial existing holdings of sovereign bonds in local banks' balance sheet. As

sovereign risk increases, the asset side of banks' balance sheet is eroded due to the decreased value of their sovereign debt holdings. Acharya et al. (2014) investigate such risk contagion mechanism as the balance sheet hit channel, which is also linked to the so called "diabolic loop" between banking and sovereign risk described in Brunnermeier et al. (2011). The balance sheet hit effect is amplified by the potential increase of banks' exposure to sovereign risk during difficult times. Banks may increase their holdings of sovereign debt during a financial crisis due to either risk-shifting as argued by Acharya et al. (2014) and Acharya and Steffen (2015) or financial repression as documented in Becker and Ivashina (2014) and Reinhart and Rogoff (2011). Sovereign risk also matters because of the collateral channel of risk transfer. Specifically, increasing sovereign risk pushes up bank risk when the value of collateral that banks hold in the form of sovereign bonds decreases. Finally, sovereign risk can spread to banks through the implicit guarantees enjoyed by financial firms, especially large banks. The value of such guarantees decreases since the ability of the authorities to support the financial system is impaired when sovereign credit conditions weaken. The policy response to the aforementioned link between public default and banking system fragility is the creation of the European Financial Stability Facility (EFSF) in 2010 with the aim of preserving financial stability by avoiding sovereign defaults.

In this paper, we investigate three related questions regarding the risk transfer from a sovereign to banks during the recent financial crises. First, is bank credit risk sensitive to sovereign credit risk and if it is, what is the magnitude of the sensitivity (multiplier) for individual banks? The answer to this question may provide useful information for bank regulation and help to make policy decisions with respect to financial repression. Second, which countries are more fragile to a "Greek style" crisis, which occurs when distressed public finances lead to distress in the banking sector? The third question we address is, what proportion of a bank's default risk comes from its exposure to systematic sovereign risk? Our

paper contributes to identifying determinants of bank credit risk, addressing the argument in Pagano and Sedunov (2014) that bank credit models should include sovereign risk as an important explanatory variable to prevent potential mis-specification errors. Theoretically, we propose a model in which sovereign default risk acts as a common factor of credit spreads of domestic banks. On the empirical side, using data from 2010 to 2013 released by European Banking Authority (EBA), we find evidence that, among other channels, the risk transmission from a sovereign to local banks works through the government bonds held by local banks.

Adopting the multifactor affine model proposed by Ang and Longstaff (2013), we find that bank default risk is indeed positively related to sovereign default risk. This finding provides further empirical support to the theoretical model in Gennaioli et al. (2014), which characterizes the relationship between public defaults and the financial sector. We also find great variation across banks in terms of their sensitivity to sovereign default risk--the multiplier of the risk transmission, which we name as credit risk Beta (c-Beta). For example, in Europe, Commerzbank has more than four times the c-Beta of Banco Santander. In the US, Citigroup's c-Beta has a value of 0.52, which is markedly different from the value of 0.12 for Bank of America.

Our analysis also shows that the US is less fragile to a "Greek style" crisis than European countries. On average, US banks' c-Beta is around 0.28, which is much smaller than that of European banks, which is about 1.01. The finding indicates that the cost of increased sovereign default risk is much lower for the US than for Europe since a US default results in less "collateral damage" to its banking system. To put it in Acharya, Drechsler and Schnabl (2014)'s words, the bailouts that intend to stabilize the financial sector may end up being a Pyrrhic victory more likely in Europe than in the US. We also show that our conclusion is not likely to be biased by the sovereign debt crisis unfolded during our sample period.

In addition, we decompose a bank's total default risk into its systematic and idiosyncratic components. The systematic part consists of a bank's c-Beta and the sovereign default intensity. During the recent sovereign debt crisis, the systematic component, which represents the risk "transferred" from a sovereign to a bank, plays a big role for banks in France, Italy and Spain. For Belgium, Germany, Switzerland and the US, bank default risk comes mainly from the idiosyncratic part during the whole time period. For banks in Sweden and the UK, it seems that the systematic part and the idiosyncratic part are more or less at the same level and the systematic part contributes more during the subprime crisis, compared with during the sovereign debt crisis.

Finally, among other factors, a bank's holdings of domestic sovereign debt should increase its sensitivity to sovereign risk (c-Beta). The stress tests and other exercises conducted by EBA provide us an opportunity to test the theory. Relying on regression analysis, we find evidence that a bank's c-Beta we extract from bank and sovereign CDS spreads is positively related to the amount of sovereign debt that the bank holds in its balance sheet. We also demonstrate the existence of a threshold of around 250 basis points of 5-year sovereign CDS spread, above which the positive relationship is established.

This paper is related to two strands of literature. The first strand studies the pricing of credit derivatives. More specifically, to model CDS spreads for sovereigns and banks, we adopt the reduced-form approach pioneered by Jarrow and Turnbull (1995).² Early important work in the area includes Black and Cox (1976), Lando (1998), Duffie (1999), Duffie and Singleton (1999) and Das and Sundaram (2000), among many others. More recently, based on a default intensity model, Longstaff et al. (2005) decompose corporate spreads into default and non-default components and conclude that the default part accounts for the majority of

² Credit derivatives are usually priced using structural models as in Merton (1974) or reduced-form models as in this paper. However, structural models can be problematic when modelling sovereign debt due to the fact that they directly capture the default incentives and solvency of the issuer, which can be far more difficult to measure for sovereigns than for corporations, as pointed out in Duffie, Pedersen and Singleton (2003).

the spread. Exploiting data from Mexico, Turkey and Korea, Pan and Singleton (2008) study the term structures of sovereign CDS spreads with a reduced-form model and separately identify both the default intensity process and the recovery rate embedded in the model. Using Pan and Singleton (2008)'s model, Longstaff et al. (2011) decompose sovereign credit risk into a default-related component and a risk-premium component and investigate the relationship between a set of global macroeconomic factors and these two components. A further utilization of a reduced-form model is found in the study of Ang and Longstaff (2013), which decomposes sovereign credit risk into a systemic component and a sovereign-specific component. Instead of investigating sovereign risk, we focus on bank risk and apply Ang and Longstaff (2013)'s model to decompose a bank's credit risk into a systematic component that is associated with sovereign risk and an idiosyncratic component that is specific to the particular bank. We identify sovereign default risk as an important determinant of bank credit risk and argue that it should be taken into consideration when pricing credit risk for banks.

The second strand of research that is closely related to our paper examines the feedback (spillover) effect between sovereign risk and bank/corporate risk. Based on Granger-causality networks and contingent claims analysis, Billio et al. (2013) propose a comprehensive approach to measure connections and risk transmission among banks, insurers and sovereigns. Their findings show that the interconnections are not symmetric and sovereigns have more influence on banks and insurers than the other way around. Exploring excess correlation, defined as correlation beyond what is accounted for by economic fundamentals, De Bruyckere et al. (2013) investigate the risk contagion between banks and sovereigns. The authors document significant evidence of contagion and find evidence of three contagion channels. Contagion effects between sovereign and bank CDS spreads are also examined in Alter and Beyer (2014), using a vector autoregressive model with exogenous common factors. Developing a self-fulfilling model where depositors', investors' and government's decisions

are determined endogenously, Leonello (2014) identify government guarantees as the generator of the two-way feedback between banking and sovereign debt crises. There is also literature that looks at only one direction of the two-way risk transfer, which is a public-to-private transfer or a private-to public transfer. Using sovereign credit ratings and stock market information, Correa et al. (2014) study the response of bank stock prices to sovereign rating changes and find that sovereign credit rating downgrades lead to negative bank stock returns, especially for those banks that are more likely to receive government support. Similarly, Bai and Wei (2012) find a statistically and economically significant spillover effect from the government to the corporate sector. With respect to the risk transfer channel, in contrast to Correa et al. (2014), the authors believe that risk spreads through the expectation that a sovereign may expropriate the private sector when facing the risk of default. Focusing on the other half of the risk transmission loop, Dieckmann and Plank (2012) find evidence of a private-to-public risk transfer and further show that the extent of such transfer is related to the importance of a country's financial system. Employing data covering 70 countries over several centuries, Reinhart and Rogoff (2011) also conclude that banking crises increase the likelihood of a sovereign crisis, with government guarantees being one possible reason. Our paper focuses on the public-to-private aspect of risk transfer between sovereigns and banks. In contrast to most of the discussed literature that examines the issue by quantifying correlation patterns, we apply a default intensity model. In this way we can deal with the endogenous dynamic nature of default intensities and avoid the typical challenge of determining the direction of causality when looking at risk transfer. In addition, our study sheds light on sovereign risk contagion to individual banks, rather than to the banking industry as a whole as in most previous literature.

The paper proceeds as follows. Section 2 sets up the methodology. Section 3 provides a description of sample selection and data sources. Section 4 presents the empirical results and Section 5 concludes. The Appendix contains proofs and derivations.

2. Methodology

In this section, we first illustrate how a bank's CDS spread can be modelled with a reduced form credit risk framework that allows for both systematic and bank-specific credit shocks. We next demonstrate how the parameters of our model are estimated by minimizing the sum of squared distance between model-based and observed values of CDS spreads.

2.1 Modelling bank CDS spreads with a systematic component

To model CDS spreads, we adopt a framework that is first introduced by Duffie and Singleton (2003) and is recently applied in Ang and Longstaff (2013) to measure systemic sovereign credit risk. Our main idea is to use the same framework to investigate the risk transfer from a sovereign to local banks. More specifically, the model defines two independent types of credit events that can trigger the default of banks and the sovereign in a country. The first one is an idiosyncratic (entity-specific) shock that leads to the default of an individual entity (it can be a bank or the sovereign). The second is a systematic shock that may have ramifications for all banks and the sovereign within the country. Both idiosyncratic and systematic shocks are modelled with Poisson processes. We assume that conditional on a systematic shock, each bank within a country has some probability of defaulting, denoted as β_i , which is bank-specific and is constant during our sample period. Similarly, the systematic shock also leads to some probability of defaulting of the sovereign, denoted as $\beta_{\text{sovereign}}$. Two identification restrictions are imposed as in Ang and Longstaff (2013). First, for each country, we normalize the sensitivity of the sovereign risk to the latent

systematic risk, $\beta_{\text{sovereign}}$, to be one and as a result the β_i for each bank in the country can be treated as relative systematic risk sensitivity. Second, it is reasonable to assume that a sovereign default can only occur in conjunction with a systematic shock for all banks in a country. We use sovereign risk and systematic risk interchangeably hereafter. As a result of the two restrictions, we interpret β_i as a bank's credit risk sensitivity to the sovereign default and we name it as c-Beta.

Let $\gamma_{i,t}$ denote the intensity of idiosyncratic or bank-specific Poisson process for bank i at time t and λ_t denote the intensity of the systematic or sovereign Poisson process. Following Longstaff et al. (2005), both intensities are assumed to follow a standard square-root process:³

$$d\gamma_{it} = (a_i - b_i\gamma_{it})dt + c_i\sqrt{\gamma_{it}}dB_{it} \quad (1)$$

$$d\lambda_t = (e - f\lambda_t)dt + g\sqrt{\lambda_t}dB_{\lambda t} \quad (2)$$

where a_i , b_i , c_i , e , f , g are model parameters and B_{it} and $B_{\lambda t}$ are uncorrelated Brownian motions.

Having set up the model, now let us look at how a bank can default within the framework. There are two sources of shocks contributing to a bank's default. First, a bank defaults the first time that there is an arrival of the bank-specific Poisson process. Second, a bank defaults with probability β_i the first time that there is an arrival of the sovereign Poisson process. A bank may survive the first systematic shock with the probability of $(1 - \beta_i)$, following which it will face the second shock which it may succumb to with the probability of default $\beta_i * (1 - \beta_i)$, and so forth. Unlike in the case of a bank's default, there is effectively only one

³ As pointed out in Ang and Longstaff (2013), the specified intensity process accommodates mean reversion and conditional heteroskedasticity and guarantees a non-negative default intensity. Also since the model allows idiosyncratic defaults across banks to be correlated, the term idiosyncratic is used in the sense of being non-systematic.

source of shock triggering sovereign's default because of our identification restrictions. Sovereign default occurs the first time there is an arrival of the sovereign Poisson process. As a result, we model sovereign credit risk with a standard univariate default model such as the one applied in Pan and Singleton (2008).

Given the properties of the Poisson process, the aforementioned default mechanism and our definitions of $\gamma_{i,t}$ and λ_t , it can be shown straightforwardly that the probability that no default occurs by time t for a particular bank is $\exp(-\int_0^t (\beta_i \lambda_s + \gamma_{is}) ds)$. Thus, the bank's total default intensity is $\beta_i \lambda_t + \gamma_{it}$, with $\beta_i \lambda_t$ representing the systematic component and γ_{it} the idiosyncratic part.⁴

Following Duffie et al. (2000) and Longstaff et al. (2005), by equating the two legs of CDS contracts, namely the protection leg and the premium leg, a closed form solution for a bank's CDS spread (b_i) can be derived. After suppressing the subscript t on λ_t and γ_{it} for notational simplicity, we have:

$$b_i = \frac{(1-R_b) \int_0^T D_t (A(\lambda,t)C(\gamma_i,t) + \beta_i B(\gamma_i,t)F(\lambda,t)) dt}{\int_0^T D_t A(\lambda,t) B(\gamma_i,t) dt} \quad (3)$$

and similarly the CDS spread for sovereigns (s_i) can be modelled as,

$$s_i = \frac{(1-R_s) \int_0^T D_t F(\lambda,t) dt}{\int_0^T D_t A(\lambda,t) dt} \quad (4)$$

where R_b and R_s are recovery rates for banks and sovereigns respectively. D_t is the risk-free discount factor, which is the present value of a risk-free zero-coupon bond with face value of 1 and maturity of t : $D(t) = E[\exp(-\int_0^t r_t dt)]$, where r_t is the risk-free rate and we assume it is independent of the intensity processes λ_t and $\gamma_{i,t}$. $A(\lambda, t)$ and $F(\lambda, t)$ are functions of λ

⁴ See Ang and Longstaff (2013) for more details.

and t and $C(\gamma_i, t)$ and $B(\gamma_i, t)$ are functions of γ_i and t . For simplicity we suppress the subscript i on γ_i, a_i, b_i and c_i . Then,

$$A(\lambda, t) = A_1(t)\exp(A_2(t)\lambda),$$

$$B(\gamma, t) = B_1(t)\exp(B_2(t)\gamma),$$

$$C(\gamma, t) = (C_1(t) + C_2(t)\gamma)\exp(B_2(t)\gamma),$$

$$F(\lambda, t) = (F_1(t) + F_2(t)\lambda)\exp(A_2(t)\lambda),$$

Where

$$A_1(t) = \exp\left(\frac{e(f+\varphi)t}{g^2}\right)\left(\frac{1-\nu}{1-\nu e^{\varphi t}}\right)^{\frac{2e}{g^2}}, \quad A_2(t) = \frac{f-\varphi}{g^2} + \frac{2\varphi}{g^2(1-\nu e^{\varphi t})}; \quad (5)$$

$$B_1(t) = \exp\left(\frac{a(b+\phi)t}{c^2}\right)\left(\frac{1-\theta}{1-\theta e^{\phi t}}\right)^{\frac{2a}{c^2}}, \quad B_2(t) = \frac{b-\phi}{c^2} + \frac{2\phi}{c^2(1-\theta e^{\phi t})}; \quad (6)$$

$$C_1(t) = \frac{a}{\phi}(e^{\phi t} - 1)\exp\left(\frac{a(b+\phi)t}{c^2}\right)\left(\frac{1-\theta}{1-\theta e^{\phi t}}\right)^{\frac{2a}{c^2}+1}, \quad C_2(t) = \exp\left(\frac{a(b+\phi)t}{c^2} + \phi t\right)\left(\frac{1-\theta}{1-\theta e^{\phi t}}\right)^{\frac{2a}{c^2}+2}; \quad (7)$$

$$F_1(t) = \frac{e}{\varphi}(e^{\varphi t} - 1)\exp\left(\frac{e(f+\varphi)t}{g^2}\right)\left(\frac{1-\nu}{1-\nu e^{\varphi t}}\right)^{\frac{2e}{g^2}+1}, \quad F_2(t) = \exp\left(\frac{e(f+\varphi)t}{g^2} + \varphi t\right)\left(\frac{1-\nu}{1-\nu e^{\varphi t}}\right)^{\frac{2e}{g^2}+2}; \quad (8)$$

And,

$$\varphi = \sqrt{f^2 + 2\beta g^2}, \quad \nu = \frac{(f+\varphi)}{(f-\varphi)}, \quad \phi = \sqrt{b^2 + 2c^2}, \quad \theta = \frac{(b+\phi)}{(b-\phi)}.$$

Detailed derivations are in the Appendix. With these closed-form solutions, we are able to fit the model with the observed term structure of CDS premia to estimate the parameters in the model.

2.2 Model estimation

We use the term structure of senior CDS spreads for each issuer (a bank or a sovereign) and for each time point over the sample period to estimate the model. We use three-year, five-year and seven-year CDS spreads in our estimation. Swap rates with the corresponding maturities are employed to calculate the risk-free discount factor in Equation (3) and (4).⁵ Following Ang and Longstaff (2013), we assume a constant loss given default (LGD) with a value of 0.5 for sovereigns. Bank LGD is set to be 0.6, which is consistent with both historical average recovery rates on senior corporate bonds reported by Moody's (see Moody's Investors Service, 2012c) and also ex-ante measures of LGD in Black et al. (2013).⁶

For each country, we first estimate the parameters of the sovereign Poisson process and the time series of the sovereign default intensity by minimizing the distance between observed and model-based values of the sovereign CDS spreads:

$$\min_{\text{parameters}} \sum_j \sum_t (s_{jt} - \widetilde{s}_{jt})^2 \quad (9)$$

in which s_{jt} is the observed sovereign CDS spread and \widetilde{s}_{jt} is the model-based spread. j is an indicator for maturity, that is three-year, five-year and seven-year. We then estimate the parameters of the bank-specific Poisson process and the time series of the idiosyncratic intensity by minimizing the following objective function for each bank:

$$\min_{\text{parameters}} \sum_j \sum_t (b_{jt} - \widetilde{b}_{jt})^2 \quad (10)$$

in which b_{jt} is the observed bank CDS spread and \widetilde{b}_{jt} is the model-based spread.

⁵ When calculating D_t on a particular day t we do so under the assumption that the risk free rate r_t is constant for the duration of the CDS contract, namely between t and T . However, r_t is allowed to vary from one day to the next.

⁶ Also see Altman (1992) and Franks and Torous (1994) for the consistent average LGD.

To estimate the parameters for the sovereign intensity process, we first set initial values for the parameters e , f and g specified in Equation (2). With these initial values, for a given time t , the CDS spread of a sovereign depends only on its default intensity λ_t as shown in Equation (4), which can be easily estimated by a non-linear least squares fit of the model to the term structure of observed CDS spreads at time t . We repeat this process for each time t throughout our sample period and calculate the value of the objective function (9) by summing up the squared distances over time. We then pick another set of values for the parameters e , f and g and redo the whole process. Iterations stop when the value of the objective function reaches its minimum. After we obtain the parameters e , f , g and λ_t , we use them as inputs to estimate the parameters for the idiosyncratic intensity process. Similarly, for each bank, we search over values of parameters a_i , b_i , c_i , and β_i until we have the minimum value of object function (10).

3. Data

We study the largest US and European banks in terms of total assets as of December 31, 2013. To select countries, we start with the United States and all Euro area countries which joined the Eurozone before 2002. We add three more countries which have large systemically important banks: Sweden, Switzerland and the United Kingdom. We then apply the following filter to each country: at least 2 of the largest banks have 3-year, 5-year and 7-year CDS prices available in Bloomberg.⁷ The screening process results in 9 countries included in our sample: Belgium, France, Germany, Italy, Spain, Sweden, Switzerland, the United Kingdom and the United States. For each country that is included we select, from its largest 5 banks, all the banks with a CDS term structure available. Our sample finally contains 29 banks, of which 4 are in the US and 25 are in Europe. We collect weekly CMA London prices of CDS

⁷ There are several different sources of CDS prices. Mayordomo et al. (2014) shows that the CMA quotes lead the price discovery process, compared with the quotes provided by other sources, such as GFI, Reuters and Markit. We employ CMA quotes.

contracts for both banks and sovereigns.⁸ Our sample covers the 321-week period from August 8, 2008 to September 26, 2014. The starting date of the sample is determined by data availability.

4. Empirical findings

We apply the methodology illustrated in Section 2 to estimate all the parameters in our model and the time-varying default intensities for banks and sovereigns. Table 1 reports parameters a , b and c of the idiosyncratic process and e , f and g of the sovereign process, together with their standard errors. In the last column of the Table, we also report the root mean squared error (RMSE) in basis points calculated from fitting the model to the chosen term structure of CDS spreads.

Consistent with the findings of Ang and Longstaff (2013) and others, we observe negative speed of mean reversion (parameter b and f) for many banks and sovereigns, which could simply be a reflection of a significant risk premium priced in the CDS contracts for the US and European banks and sovereigns. This is because our model is estimated under the risk-neutral measure rather than the objective measure. It is also worth noting that the model fits very well both the term structure of bank CDS spreads and the term structure of sovereign CDS spreads. The last column of Table 1 shows that for sovereigns, the RMSEs are all less than 15 basis points, ranging from as low as 3 basis points for Sweden to a high of about 14 basis points for Italy, with an average of less than 8 basis points. Similarly, if we look at the RMSEs for banks, our model fits observed bank CDS spreads closely. During the sample period, the average CDS spreads across all banks and all maturities is around 177 basis points. The majority of RMSEs from fitting the term structure of bank CDS spreads are around 10 basis points, with the highest value of less than 24 basis points.

⁸ The notional for the US sovereign CDS contract is denominated in Euros and the notional for the US bank CDS contracts is denominated in dollars. Similarly, the notional for the European sovereign CDS contract is denominated in dollars and the notional for the European bank CDS contracts is denominated in Euros.

The next step is to look at the model implied risk-neutral default intensities for both sovereigns and banks in our sample. We then investigate the sensitivity of bank default risk to domestic sovereign default risk at bank level and also at country level— c -Beta and aggregate c -Beta, following which we examine the systematic component of a bank's default risk. Finally, using data released by the EBA, we empirically confirm one of the risk transmission channels from a sovereign to local banks.

4.1 Risk-neutral default intensities for sovereigns and banks

4.1.1 Sovereign default intensity

Figure 1 displays the time series of the default intensity of the sovereign Poisson process λ_t for each country. We divide countries into two groups: low risk group and high risk group. A country is classified as low risk if its 5-year CDS spread is never higher than 200 basis points during our sample period and it is high risk otherwise.⁹ Figure 1.A reports the default intensities for high risk countries and those of low risk countries are plotted in Figure 1.B.

All countries in the high risk group are within the Eurozone, while low risk group includes the US, European countries outside the Euro area and Germany. As shown in Figure 1, in general, sovereign default intensities move in the same direction, which is reflected in an average pairwise correlation of 0.90 for the high risk group and 0.71 for the low risk group during our sample period. This is consistent with the findings in Longstaff et al. (2011). Let us first look at countries in the high risk group as shown in Figure 1.A. The default risk increases substantially during the period spanning the last quarter of 2008 and the first quarter of 2009 due to the subprime crisis initiated in the US. The risk decreases to the pre-crisis level afterwards and remains low and stable for a short time period before it soars again from December 2009. The second round of dramatic increase in default risk happens during the end

⁹ The barrier of 200 basis points is chosen so that we split our sample evenly.

of 2009 to the middle of 2012. Very likely, it results from the deteriorating public finances and the weakened economic growth of these Eurozone countries. The worst cases are Spain and Italy, whose default intensities reach their record high in June 2012 at around 950 basis points and 850 basis points, respectively. Those values of default intensity are, approximately, equivalent to a one-year risk-neutral probability of default of $1 - \exp(-0.095) = 0.091$ and $1 - \exp(-0.085) = 0.081$. It is also worth noting that, although all countries in the high risk group move closely and are at a similar level in terms of default risk during the subprime crisis, Italy and Spain as a sub-group seem to behave differently from Belgium and France during the following European debt crisis. Turning to Figure 1.B, it shows that low risk countries experience the pattern and level of default risk similar to those of high risk countries during the subprime crisis. However it is evident that the European sovereign debt crisis has much less impact on the default prospects of low risk countries than those of high risk ones. This may indicate that the sovereign debt crisis was felt mainly within Eurozone, especially in the peripheral countries like Spain and Italy in our sample.

4.1.2 Bank default intensity

In this paper, bank default intensity is modelled as a combination of sovereign default intensity and idiosyncratic default intensity, namely $\beta_i \lambda_t + \gamma_{it}$. Figure 2 displays the time series of the average bank default intensity for each country. There are two peaking areas of bank default risk, corresponding to the two financial crises at the beginning of the 21st century. This feature is more evident for high risk countries as shown in Figure 2.A than for low risk countries presented in Figure 2.B. Interestingly, despite rather low sovereign default risk, German banks have an average default probability as high as $1 - \exp(-0.098) = 0.093$ in December 2008 during the subprime crisis, which is driven by bank-specific shocks. On the other hand, Spanish banks perform relatively well during the European sovereign debt

crisis, given the high default risk of the country. From next section, we focus on the systematic component of bank default risk $\beta_i \lambda_t$ and we start with β_i (c-Beta), the key parameter in this paper.

4.2 Bank credit risk Beta (c-Beta)

The recent European sovereign debt crisis has reminded us that a bank's credit risk can be quite sensitive to sovereign risk and the "vicious spiral" between them can generate enormous costs to the real economy and pose great challenges to regulators. By exploring information in the CDS market, we propose a measure of the multiplier of sovereign-bank risk transmission: c-Beta. Table 2 contains the estimated c-Beta and the standard errors for each bank in the sample. Our first finding is that the value of c-Beta is positive and significant for all banks, which confirms the impression that sovereign default risk increases bank default risk. On the other hand, banks are quite different from each other in terms of the magnitude of their c-Beta. For example, in the US, the most sensitive bank during the sample period is Citigroup, which has a c-Beta more than four times the c-Beta of Bank of America. Similarly, in Europe, the largest c-Beta belongs to Commerzbank in Germany, with a value of 2.391. In contrast, Caixabank in Spain, whose c-Beta is only 0.076, is much less fragile to sovereign risk. The difference in c-Beta can come from a variety of sources. First, banks with more holdings of sovereign debt should have larger c-Beta due to the asset holdings effect and collateral effect as described in Section 1. We explicitly examine this relationship in Section 4.5. Second, governments can influence banks and force them to hold more sovereign debt during crisis through direct government ownership or board representation, among other channels (financial repression). Thus, banks that are more likely to be "used" by governments to exercise financial repression during difficult times should be more sensitive to sovereign risk. In other words, all else being equal, a bank with higher government ownership or/and more government board seats should have larger c-Beta. Third, if a bank actively hedges out

its sovereign exposure through financial risk management, it should be less sensitive to a sovereign default. Therefore a bank in a safe country, such as Germany, may have high c-Beta, since it does not hedge due to the general perception that the country's sovereign debt is rather safe. Our findings may have policy implications. On the one hand, high c-Beta banks should be encouraged to reduce their exposure to sovereign debt. One possible solution is to link the risk weight of sovereign bonds to a bank's c-Beta when calculating the bank's capital requirement. In other words, rather than applying a universal risk weight for domestic sovereign debt holdings as in Basel III, bank-specific risk weight attached to c-Beta could provide the right incentive for banks to manage their risk. On the other hand, governments should take into consideration banks' capacity to bear more sovereign exposure, when they "need" to exercise financial repression for the broader interest. As a measure of such capacity, c-Beta could facilitate governments' decision-making.

4.3 c-Beta at country level

We also look at aggregate c-Beta for each country with the objective of identifying which country is more susceptible to a "Greek-style" crisis. We measure aggregate c-Beta as the average of individual c-Beta across all banks in a country. Table 3 shows that the values of aggregate c-Beta are quite different both across regions and also across countries. Comparing the US with Europe, aggregate c-Beta in the US is around one quarter of that in Europe, which suggests that sovereign risk in the US is much less a concern for banks than in Europe. Within Europe, interestingly, banks in Eurozone have on average lower c-Beta than their non-Eurozone counterparts, indicating that the difference between Europe and the US in terms of c-Beta is not due to the sovereign debt crisis originated in Europe and hit Eurozone the most. In particular, countries like Germany and Switzerland, which have been perceived to be relatively safe during the sample period, have quite high aggregate c-Beta. Our findings suggest that banks in these safe countries might be more fragile to sovereign risk than their

counterparts in riskier countries. In other words, banks in Germany would suffer even more than banks in Italy if Germany was as risky as Italy. One reason could be that, as discussed in Section 4.2, banks in riskier countries actively manage their sovereign exposure and thus end up with lower c-Beta. An alternative explanation relates to the findings in Gennaioli et al. (2014). Specifically, countries with higher aggregate c-Beta are more motivated to keep the probability of public default low because of their concern about post-default declines in private credit, which is more severe than for countries with lower aggregate c-Beta. The policy implication is that, compared with low c-Beta countries, it is more important for high c-Beta countries to keep their credit condition healthy because deteriorated sovereign credit can quickly translate into higher default risk in their banking system through the high multiplier of risk transmission.

4.4 Systematic component of bank default risk

It would be of great interest for both academics and policy makers to look at how large the systematic component of a bank's default risk is and how it evolves over time. One advantage of our model is its ability of decomposing the instantaneous bank default risk into two parts: the systematic component $\beta_i \lambda_t$ and the idiosyncratic component γ_{it} . Figure 3 shows the evolution of both components for all countries over our sample period. It is clear that on average, during the sovereign debt crisis of 2009-2012, the systematic component (the red area) plays a dominating role for banks in France, Italy and Spain. Since the systematic component represents the part of bank risk that is "transferred" from sovereign risk, this finding is consistent with the fact that these countries suffered the most from the sovereign debt crisis compared with the remaining countries in our sample. In contrast, for banks in Belgium, Germany, Switzerland and the US, their credit risk comes mainly from the idiosyncratic part (the blue checked area) during the whole sample period. Combined with the fact that the c-Beta is relatively high for Germany and Switzerland, the low systematic

component--the product of c-Beta and sovereign default intensity--is largely due to the low sovereign risk in these countries. Lastly, for British and Swedish banks, it seems that the systematic part and the idiosyncratic part are more or less at the same level. Unlike the banks in the Eurozone, the systematic component of banks in these two countries is highest in terms of both absolute value and also as a percentage to total default intensity during the subprime crisis rather than the European sovereign debt crisis. This may reflect the fact that the UK and Sweden are not members of Eurozone and thus are much less affected by the sovereign debt crisis and the consequent threat to the integrity of the Euro.

4.5 Risk transmission channels

As demonstrated in Section 4.2, a bank's c-Beta depends on several factors, such as 1) its holdings of sovereign debt, 2) the potential pressure a country can exert on the bank to buy more sovereign debt during a crisis and 3) its risk management strategy regarding sovereign debt. The last two factors can be too subtle to measure accurately and we do not possess the data to proxy them.¹⁰ Nevertheless, data regarding bank holdings of local government debt are available from the EBA. Therefore, we are able to investigate the relationship between c-Beta and the first factor. A positive relationship between them can also corroborate our previous finding that c-Beta is a measure of bank credit sensitivity to sovereign risk.¹¹ Specifically, we collect data of bank sovereign debt holdings from the EBA's 2010, 2011 and 2014 Stress Tests, 2011 and 2012 Capital Exercise and 2012 and 2013 Transparency Exercise. The bank level data are available for 20 out of 25 European banks in our sample and covers the period between March 2010 and December 2013, with 7 snapshots in total. Figure 4

¹⁰One could argue that the second factor could be reflected in the first one, at least partially. In other words, the extent to which a country can exert financial repression to a bank is positively related to the bank's holdings of sovereign debt during the crisis periods.

¹¹ Our intention is to corroborate our estimate of c-Beta, using banks' balance sheet information and indicate one channel that directly transfers risk from a sovereign to local banks, instead of providing a complete picture of the risk transmission mechanism.

reveals the first impression of a positive relationship between a bank's c-Beta and its sovereign debt holdings. In general, the positive relationship seems to hold for all countries except Spain. To further examine the question, we estimate the following regression:

$$\begin{aligned} \text{Systematic Component}_{i,t} = & \alpha + \beta_1 \text{SovExp}_{i,t} + \beta_2 \text{VIX}_t + \beta_3 \text{Ccredit}_{j,t} + \beta_4 \text{SovExp}_{i,t} * \\ & \text{Ccredit}_{j,t} + \beta_5 \text{SovExp}_{i,t} * \text{Bcredit}_{i,t} + \sum_j \theta_j C_j + \varepsilon_{i,t} \end{aligned} \quad (11)$$

In Equation (11), the subscripts i, j and t denote a bank, a country and time respectively. The dependent variable systematic component is the product of c-Beta and sovereign default risk, namely $\beta_i \lambda_t$. SovExp is the variable of interest, which is measured as a bank's holdings of sovereign debt divided by its total equity. VIX and Ccredit are included as control variables. We use VIX, the implied volatility on the S&P 500, as a proxy for market risk aversion. Ccredit is a proxy for sovereign risk, measured as a country's 5-year CDS spread. C_j is a dummy variable for country j. The interaction term multiplying SovExp with Ccredit is also of great interest because bank default risk may only be sensitive to sovereign default risk when the market begins to worry about sovereign risk, i.e. when sovereign risk is higher than a certain threshold. Similarly, the level of default risk of a bank itself may also play a role in determining the coefficient of SovExp. The idea is that when a bank is safe enough, the risk of holding risky sovereign debt may not be priced into its CDS contracts. We include another interaction term $\text{SovExp}_{i,t} * \text{Bcredit}_{i,t}$ in the regression to examine this hypothesis. Bcredit is a proxy for bank default risk, measured as a bank's 5-year CDS spread.

We are aware that the dependent variable (systematic component) comes from a first-stage estimation, which may introduce measurement error and, as a result, heteroscedasticity. Since we do not obtain detailed information about the possible measurement error, we use White period standard errors (standard errors adjusted for clustering at the firm level) to account for heteroscedasticity (as in Weiß et al., 2014), as well as possible autocorrelation within firms in

the regression's residuals (see Petersen, 2009).¹² Table 4 displays the results of the regressions. The univariate regression in column 1 suggests that banks holding more sovereign debt on their balance sheet are more sensitive to systematic/sovereign risk. Since market risk appetite may have a role to play in determining the risk-neutral systematic component and at the same time is related to banks' holdings of sovereign debt, we control for it in column 2 by adding VIX as an independent variable. The coefficient of SovExp remains positive and significant. As one would expect, market risk aversion is positively related to the systematic component, probably through λ_t . More specifically, we are interested in the relationship between c-Beta, which is only one part of the whole systematic component $\beta_i \lambda_t$, and SovExp.¹³ Therefore, we need to control for the other part of the component—the sovereign risk. Adding the control variable Ccredit--the five year sovereign CDS spread--in column 3 does not change the positive sign of the SovExp variable, although its significance falls to the 5% level.

A potential endogeneity issue which could bias our results is associated with the risk-shifting behaviour of banks as described in Acharya et al. (2014). As the domestic sovereign become riskier, banks with higher default risk have stronger incentives to engage in risk-shifting by buying additional domestic sovereign debt because 1). It offers relatively high return and at the same time it is exempt from regulatory capital charge; and 2). Sovereign debt only generates large losses in disaster scenarios in which banks holding it will not fully bear the cost because of limited liability and explicit and implicit public guarantees. As a result, the positive coefficient of SovExp might just be a simple reflection of such risk-shifting. In other words, our result may not imply that holding more sovereign debt leads to

¹² Unreported results of robustness tests using various standard errors confirm that White period standard errors are the most conservative.

¹³ We could run regressions with c-Beta, rather than the whole systematic component, as the dependent variable. However, since c-Beta is constant over time as defined in our model, this would significantly reduce our sample from 140 to 20, thus reducing our ability to make meaningful reference with our regressions.

higher c-Beta. It is also possible that banks with higher systematic default risk choose to hold more sovereign bonds. To address this endogeneity concern, more specifically the simultaneity bias issue as described in Roberts and Whited (2012), we conduct sub-sample regression analysis with only Eurozone banks. If the risk-shifting effect indeed plays a dominant role, we would expect a larger and more significant coefficient of SovExp for the sub-sample because it is more “valuable” to risk-shift for banks in riskier Eurozone countries, compared with those in non-Eurozone countries. In Table 4, comparing specification 3 (the whole sample) with specification 4 (the Eurozone sub-sample), we observe no significant difference between the two coefficients of SovExp (5.94 vs. 6.17). To further investigate the issue, we introduce an interaction term (SovExp*EZ) into specification 3 for the whole sample. EZ is a dummy variable representing banks in Eurozone. The negative and insignificant coefficient of the interaction term as displayed in column 5 of Table 4 continues to deny the risk-shifting effect and to support our conclusion that banks holding more sovereign debt have higher c-Beta.

It is reasonable to believe that other factors which can also influence the c-Beta, such as the government’s attitude towards using local banks to share public financial burdens during a crisis and political culture, are country-specific. To account for these potential factors that may also be spuriously associated with SovExp, we include country dummy variables in our regression analysis. The results in column 6 shows that after controlling for all time-invariant differences among countries, SovExp still has a positive and significant coefficient.

One may argue that when sovereign bonds are almost risk-free, banks with a larger amount of such safe assets should not be riskier. In particular, holding more sovereign debt may not lead to an increased c-Beta at all unless the sovereign debt is risky to some extent. Put it differently, there might be a “wake-up call” that activates the relationship between c-Beta and sovereign debt holdings. To examine the hypothesis, we introduce an interaction term

between SovExp and Ccredit in column 7. Interestingly, the coefficient of SovExp becomes negative and insignificant. As we would expect, the coefficient of the interaction term is positive and significant at the 5% level. The combination of these findings confirms the “wake-up call” idea. It seems from our analysis that the c-Beta is positively related to SovExp only when the 5-year sovereign CDS premium is higher than around 250 basis points (the cut-off point is $3.981/0.017=236$ as specified in column 7 and it is $6.252/0.024=261$ as specified in column 8). Approximately, the CDS spread of 250 basis points translates into a risk-neutral default probability of $0.025/0.5=0.05$ ($PD \doteq \frac{CDS\ spread}{LGD}$) for a country over the next year. As shown in Figure 5.A, this threshold is first reached by Italy and France in our high risk country group in May 2010, when Greece receives its first bailout. Since then the two countries have remained in the “sensitive region” until October 2013. Belgium and France join them later during the heat of the European sovereign debt crisis (2011 to 2012). It seems that for countries in our low risk group presented in Figure 5.B, like the UK and Germany, the relationship between the c-Beta and sovereign debt holdings was not established during our sample period. In other words, the “wake-up call” was never made. In addition, as shown in Figure 5, compared with the European sovereign debt crisis, the subprime crisis is less damaging in the sense that sovereign risk is relatively low across all countries in both groups. Under these circumstances holding sovereign bonds should not increase the c-Beta of banks. On the other hand, if a bank itself is safe to some extent, its holdings of sovereign debt may not trigger the “wake-up call” either. We investigate the interaction term SovExp*Bcredit instead of SovExp*Ccredit in column 9 and 10. Bcredit represents the default risk for banks and is proxied with the 5-year bank CDS spread. As shown in the last two columns of Table 4, the cut-off point is about 450 basis points ($11.321/0.025=453$ in column 9 and $9.203/0.022=418$ in column 10, respectively). We conduct robustness tests by adding firm fixed effects instead of using country dummies to

account for the fact that time-invariant differences may exist at firm level rather than at country level. In addition, although we include the firm-invariant variable VIX to capture common factors across firms, it is still possible that we may miss other important time-specific explanatory variables. As a result, we replace VIX with time fixed effects to capture potential observable and unobservable factors that jointly determine the c-Beta. The robustness test results are contained in column 8 and 10 and it is clear that our findings remain unchanged.

Banks have long been encouraged to hold sovereign debt in their balance sheet by an attractive capital treatment in terms of a low risk weight (zero) carried by sovereign bonds since Basel I in 1988. However, a careful investigation regarding the impact of holding such debt on bank risk is warranted as a result of the European sovereign debt crisis. Findings in column 1 through 6 in Table 4 suggest that holding sovereign debt can increase the systematic component of bank default risk and also a bank's sensitivity to sovereign risk, the c-Beta. Therefore, sovereign debt held by local banks act as an important media that transfers risk from sovereign to banks. On the other hand, results in column 7 through 10 of the same table show that as long as the sovereign credit risk or bank credit risk is lower than certain thresholds, holding more sovereign bonds will not increase the sensitivity c-Beta and thus will not exacerbate the risk transmission mechanism.

5. Conclusions

The recent European debt crisis has shown us how import it is to bring sovereign risk under control. Even for developed countries in Europe, their debt can become rather risky and the risk can be transmitted to the banking system easily and quickly. A practical measure of banks' sensitivity to sovereign risk, such as the c-Beta proposed in this paper, could be a first step to manage sovereign risk and reduce its repercussions through the banking system.

Our analysis suggests that c-Beta can be very different for banks in both the US and Europe during the period 2008 to 2014. Interestingly, banks in low risk countries may have higher c-Beta than those in relatively high risk countries. At country level, the US has much lower risk of suffering a “Greek style” crisis than most European countries. We also find that a bank’s c-Beta is positively related to its holdings of sovereign debt, which is a direct channel that passes on risk from sovereigns to banks. Importantly, the c-Beta increases with sovereign debt holdings only when a country’s sovereign risk reaches a certain barrier. Consequently, a country would benefit from keeping its default risk lower than the “wake-up call” point, which is about 250 basis points of the 5-year sovereign CDS spread.

The results in the paper have policy implications. In a speech given at the Financial Stability Institute High-Level Meeting in October 2011, the deputy general manager of the BIS, Herve Hannoun, pointed out “...sovereign assets...should no longer be assigned a zero risk weight and must be subject to a regulatory capital charge differentiated according to their respective credit quality.” To design a bank-specific capital charge scheme for holding sovereign assets, our c-Beta estimate, the “multiplier” of the risk transmission mechanism, could provide additional information beyond sovereign assets’ credit quality. Second, banks with high c-Beta should be monitored closely and be encouraged to reduce their exposure to sovereign debt by reducing their holdings of sovereign debt or through risk hedging. Finally, during crisis periods, when governments are tempted to expropriate the private sector, in particular to “allocate” sovereign debt across domestic banks, they may want to take into consideration the heterogeneity across banks in terms of their fragility to sovereign debt--the magnitude of their c-Beta.

Appendix. Pricing CDS contracts with a multifactor affine framework

There are two parties that are involved in a CDS contract, the protection buyer and the protection seller. A CDS contract is similar to an insurance contract in the sense that it protects the buyer from losses arising from a default by the reference entity. More specifically, to buy the protection, the buyer pays a periodic (usually quarterly or semi-annually) premium until the maturity of the contract or the occurrence of a credit event defined in the contract, whichever comes sooner. In return, the protection seller promises to compensate the difference between the face value and the market value of the reference issue in the event of a default.¹⁴

Among others, Duffie (1998), Lando (1998), Duffie and Singleton (1999) show that a CDS contract can be priced by equating the two legs of the contract: the premium leg and the protection leg. Let b_i denote the CDS spread for bank i . Assuming the premium is paid continuously, the present value of the premium leg (PreLeg) can be written as:

$$PreLeg = E[b_i \int_0^T D(t) \exp(-\int_0^t \beta_i \lambda_s + \gamma_{i,s} ds) dt] \quad (A.1)$$

Similarly, the present value of the protection leg (ProLeg) can be derived as:

$$ProLeg = E[(1 - R) \int_0^T D(t) (\beta_i \lambda_t + \gamma_{i,t}) (\exp(-\int_0^t \beta_i \lambda_s + \gamma_{i,s} ds) dt)] \quad (A.2)$$

At the time that a CDS contract is issued, the two legs should be identical, namely:

$$PreLeg = ProLeg \quad (A.3)$$

We can solve out the b_i from Equation (A.3), which will give us Equation (3) in the paper. More specifically, Equation (3) is derived following the method in Ang and Longstaff (2013). After rearranging items, Equation (A.2) can be expressed as:

¹⁴ See Pan and Singleton (2008) and Dieckmann and Plank (2012) for more details about CDS contracts, especially sovereign CDS contracts.

$$\begin{aligned}
ProLeg = & (1 - R)D(t)E \left[\exp \left(- \int_0^t \beta \lambda_s ds \right) \right] E \left[\gamma_t \exp \left(- \int_0^t \gamma_s ds \right) \right] + \\
& \beta E \left[\exp \left(- \int_0^t \gamma_s ds \right) \right] E \left[\lambda_t \exp \left(- \int_0^t \beta \lambda_s ds \right) \right]
\end{aligned} \tag{A.4}$$

If we denote the four expectations in Equation (A.4) in order as follows:

$$\begin{cases} E \left[\exp \left(- \int_0^t \beta \lambda_s ds \right) \right] : & A(\lambda, t) \\ E \left[\gamma_t \exp \left(- \int_0^t \gamma_s ds \right) \right] : & C(\gamma, t) \\ E \left[\exp \left(- \int_0^t \gamma_s ds \right) \right] : & B(\gamma, t) \\ E \left[\lambda_t \exp \left(- \int_0^t \beta \lambda_s ds \right) \right] : & F(\lambda, t) \end{cases},$$

The first expectation $A(\lambda, t)$ satisfies the partial differential equation (PDE), as in Cox, Ingersoll and Ross (1985) and Ang and Longstaff (2013):

$$\frac{\sigma^2}{2} \lambda A_{\lambda\lambda} + (e - f\lambda)A_\lambda - \beta\lambda A - A_t = 0 \tag{A.5}$$

subject to the boundary condition $A(\lambda, 0)=1$. $A_{\lambda\lambda}$ represents the second order derivative of $A(\lambda, t)$ with respect to λ and similarly A_λ is the first order derivative. A_t represents the first order derivative of $A(\lambda, t)$ with respect to time t . If we express $A(\lambda, t)$ as $A_1(t)\exp(A_2(t)\lambda)$, we can differentiate this expression and substitute the results into Equation (A.5). It can be shown that PDE (A.5) is satisfied as long as $A_1(t)$ and $A_2(t)$ satisfy the following Riccati equations:

$$A_2' = \frac{\sigma^2}{2} A_2^2 - fA_2 - \beta,$$

and $A_1' = eA_2A_1$, subject to the initial conditions $A_1(0) = 1$ and $A_2(0) = 0$.

A_2' and A_1' represent the first order derivative of $A_2(t)$ and $A_1(t)$, respectively, with respect to time t . Solving these two bounded ordinary differential equations gives us $A_1(t)$ and $A_2(t)$

in Equation (5) in the paper. Representing the third expectation $B(\gamma, t)$ as $B_1(t)\exp(B_2(t)\gamma)$, the same procedure can be used to derive $B_1(t)$ and $B_2(t)$ in Equation (6).

Similarly, the fourth expectation $F(\lambda, t)$ satisfies the same PDE as in Equation (A.5), with A replaced by F . Expressing $F(\lambda, t)$ as $(F_1(t) + F_2(t)\lambda)\exp(A_2(t)\lambda)$, we can substitute it into the PDE. It can be shown that the following two Riccati equations should be satisfied:

$$F_2' = (e + \sigma^2)A_2F_2 - fF_2,$$

$$F_1' = eF_2 + eF_1A_2,$$

subject to the initial conditions $F_1(0) = 0$ and $F_2(0) = 1$. F_2' and F_1' represent the first order derivative of $F_2(t)$ and $F_1(t)$, respectively, with respect to time t . Solving these two bounded ordinary differential equations gives us $F_1(t)$ and $F_2(t)$ in Equation (8) in the paper. Expressing the second expectation $C(\gamma, t)$ as $(C_1(t) + C_2(t)\gamma)\exp(B_2(t)\gamma)$, the same procedure can be used to derive $C_1(t)$ and $C_2(t)$ in Equation (7).

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Table 1. Parameter estimates

| | Parameter | | | Standard error | | | RMSE |
|--------------------|-----------|----------|---------|----------------|---------|---------|--------|
| | a (e) | b (f) | c (g) | a (e) | b (f) | c (g) | |
| KBC | 0.00352 | -0.31895 | 0.34472 | 0.00006 | 0.00884 | 0.00582 | 15.697 |
| Dexia | 0.00857 | 0.15141 | 0.02492 | 0.00020 | 0.02345 | 0.27799 | 23.512 |
| Belgium | 0.00197 | -0.31509 | 0.25921 | 0.00003 | 0.00505 | 0.00348 | 10.253 |
| BNP Paribas | -0.00032 | -0.77734 | 0.20921 | 0.00002 | 0.01749 | 0.00575 | 13.639 |
| Credit Agricole | -0.00012 | -0.87848 | 0.23181 | 0.00002 | 0.01875 | 0.00559 | 14.135 |
| Soc Generale Sa | 0.00026 | -0.85669 | 0.36339 | 0.00004 | 0.03922 | 0.01614 | 14.408 |
| Natixis | -0.00082 | 0.01727 | 0.10348 | 0.00007 | 0.11253 | 0.31484 | 12.287 |
| France | 0.00058 | -0.48254 | 0.19956 | 0.00002 | 0.00494 | 0.00251 | 9.495 |
| Deutsche Bank | 0.00047 | -0.85707 | 0.33699 | 0.00002 | 0.01844 | 0.00657 | 10.997 |
| Commerzbank | -0.00056 | -0.54981 | 0.15002 | 0.00002 | 0.01177 | 0.00539 | 12.615 |
| IKB | 0.01327 | 0.25409 | 0.13560 | 0.00121 | 0.14216 | 0.31516 | 16.424 |
| Germany | 0.00029 | -0.50756 | 0.18064 | 0.00001 | 0.00579 | 0.00272 | 5.970 |
| Unicredit | -0.00073 | -0.52402 | 0.22806 | 0.00003 | 0.01317 | 0.00607 | 14.159 |
| Intesa Sanpaolo | -0.00105 | -0.34689 | 0.18206 | 0.00003 | 0.01450 | 0.01005 | 12.773 |
| Banca Monte Dei | -0.00208 | -0.00616 | 0.00154 | 0.00008 | 0.04171 | 6.72118 | 14.572 |
| Banco Popolare | -0.00168 | -0.02577 | 0.00242 | 0.00007 | 0.03755 | 3.62752 | 14.283 |
| Italy | 0.00311 | -0.18156 | 0.21702 | 0.00006 | 0.00377 | 0.00370 | 13.876 |
| Banco Santander | -0.00013 | -0.94691 | 0.20871 | 0.00001 | 0.01314 | 0.00343 | 11.824 |
| BBVA | -0.00014 | -0.84077 | 0.22765 | 0.00001 | 0.01656 | 0.00514 | 11.232 |
| Caixabank | 0.00288 | -0.14866 | 0.26151 | 0.00020 | 0.06062 | 0.03323 | 10.178 |
| Spain | 0.00297 | -0.14474 | 0.20465 | 0.00005 | 0.00346 | 0.00377 | 13.120 |
| SEB | 0.00012 | -0.82389 | 0.27006 | 0.00002 | 0.00967 | 0.00330 | 9.546 |
| Svenska Han | -0.00051 | -0.57010 | 0.16181 | 0.00006 | 0.02275 | 0.02604 | 6.510 |
| Swedbank | 0.00143 | -0.06355 | 0.16815 | 0.00007 | 0.02752 | 0.03207 | 7.714 |
| Sweden | 0.00067 | -0.48405 | 0.26079 | 0.00001 | 0.00411 | 0.00203 | 3.103 |
| UBS | 0.00004 | -0.85982 | 0.21831 | 0.00001 | 0.01144 | 0.00303 | 8.627 |
| Credit Suiss | 0.00001 | -0.94451 | 0.21670 | 0.00001 | 0.01082 | 0.00255 | 9.246 |
| Switzerland | 0.00143 | -0.40246 | 0.30340 | 0.00001 | 0.00697 | 0.00385 | 3.986 |
| HSBC | -0.00030 | -0.71566 | 0.17446 | 0.00001 | 0.00890 | 0.00308 | 8.849 |
| Barclays | -0.00012 | -0.81690 | 0.19462 | 0.00001 | 0.01271 | 0.00387 | 12.307 |
| RBS | -0.00008 | -0.73447 | 0.24283 | 0.00002 | 0.02538 | 0.00943 | 14.804 |
| Lloyds | -0.00065 | -0.32310 | 0.19050 | 0.00004 | 0.04423 | 0.03460 | 13.202 |
| UK | 0.00090 | -0.57487 | 0.27436 | 0.00002 | 0.00632 | 0.00280 | 5.909 |
| JPMorgan Chase | 0.00105 | -0.97198 | 0.35339 | 0.00002 | 0.01056 | 0.00336 | 8.805 |
| Bank of America | 0.00359 | -0.37003 | 0.36150 | 0.00012 | 0.02967 | 0.01087 | 11.301 |
| Citigroup | 0.00156 | -1.04873 | 0.39024 | 0.00003 | 0.01238 | 0.00383 | 9.299 |
| Wells Fargo | 0.00077 | -1.13224 | 0.35262 | 0.00001 | 0.00818 | 0.00239 | 7.323 |
| US | 0.00111 | -0.13429 | 0.18177 | 0.00002 | 0.00818 | 0.00827 | 3.892 |

This Table reports the parameter estimates for the CDS pricing model in the paper, more concretely the estimates for parameters of the default intensity processes as in Equation (1) and (2). The parameters a, b and c are reported along with each bank and the parameters e, f and g are reported along with each country. The root mean squared error (RMSE) is also reported in the Table for both banks and countries. The parameters are estimated from weekly CDS spreads during the 2008 to 2014 period.

Table 2. Bank credit risk Beta

| Country | Bank | c- Beta | Standard error |
|----------------|-----------------|----------------|-----------------------|
| Belgium | KBC | 0.101 | 0.005 |
| | Dexia | 0.064 | 0.007 |
| France | BNP Paribas | 0.905 | 0.011 |
| | Credit Agricole | 1.328 | 0.014 |
| | Soc Generale Sa | 1.308 | 0.014 |
| | Natixis | 1.129 | 0.011 |
| Germany | Deutsche Bank | 1.344 | 0.023 |
| | Commerzbank | 2.391 | 0.030 |
| | IKB | 0.980 | 0.032 |
| Italy | Unicredit | 0.696 | 0.003 |
| | Intesa Sanpaolo | 0.612 | 0.003 |
| | Banca Monte Dei | 0.727 | 0.004 |
| | Banco Popolare | 0.846 | 0.004 |
| Spain | Banco Santander | 0.554 | 0.002 |
| | BBVA | 0.567 | 0.002 |
| | Caixabank | 0.076 | 0.002 |
| Sweden | SEB | 1.276 | 0.019 |
| | Svenska Han | 0.925 | 0.011 |
| | Swedbank | 1.529 | 0.017 |
| Switzerland | UBS | 1.905 | 0.021 |
| | Credit Suiss | 1.235 | 0.018 |
| UK | HSBC | 0.864 | 0.011 |
| | Barclays | 1.590 | 0.022 |
| | RBS | 1.226 | 0.024 |
| | Lloyds | 1.061 | 0.019 |
| US | JPMorgan Chase | 0.208 | 0.018 |
| | Bank of America | 0.121 | 0.022 |
| | Citigroup | 0.517 | 0.021 |
| | Wells Fargo | 0.258 | 0.015 |

This Table reports the estimated value of credit risk Beta (c-Beta) for all banks in our sample. The c-Beta is estimated from weekly CDS spreads during the 2008 to 2014 period.

Table 3. Aggregate credit risk Beta

| | Belgium | France | Germany | Italy | Spain | Sweden | Switzerland | UK | Europe | Eurozone | US |
|------------------|---------|--------|---------|-------|-------|--------|-------------|-------|--------|----------|-------|
| Aggregate c-Beta | 0.082 | 1.167 | 1.572 | 0.720 | 0.399 | 1.243 | 1.570 | 1.185 | 1.010 | 0.79 | 0.276 |

This Table reports the aggregate credit risk Beta for all countries in our sample. The aggregate c-Beta is calculated as the average c-Beta across banks in a country. For Europe, it is averaged across banks in Europe.

Table 4. Risk transmission through sovereign debt holdings

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---------------------|---------------------|----------------------|----------------------|---------------------|----------------------|-----------------------|-----------------------|--------------------|----------------------|--------------------|
| Constant | 69.58*** (0.000) | -68.08*** (0.000) | -40.64*** (0.002) | -48.76** (0.005) | -41.04*** (0.000) | -130.97*** (0.000) | -116.52*** (0.000) | -4.58 (0.870) | -106.06** (0.000) | -3.76 (0.895) |
| SovExp | 18.71*** (0.000) | 18.27*** (0.000) | 5.94** (0.020) | 6.17** (0.021) | 17.74* (0.091) | 1.94** (0.031) | -3.98 (0.230) | -6.25 (0.172) | -11.32 (0.148) | -9.20 (0.180) |
| EZ*SovExp | | | | | -11.74 (0.252) | | | | | |
| VIX | | 7.59*** (0.000) | 1.28 (0.133) | 1.26 (0.342) | 1.09 (0.246) | 0.40 (0.382) | 0.51 (0.300) | | 0.65 (0.209) | |
| Ccredit | | | 0.78*** (0.000) | 0.80*** (0.000) | 0.79*** (0.000) | 0.91*** (0.000) | 0.84*** (0.000) | 0.80*** (0.000) | 0.82*** (0.000) | 0.80*** (0.000) |
| Country dummy | | | | | | Yes | Yes | | Yes | |
| SovExp*Ccredit | | | | | | | 0.02** (0.039) | 0.02** (0.031) | | |
| SovExp*Bcredit | | | | | | | | | 0.03* (0.089) | 0.02* (0.071) |
| Firm fixed effects | | | | | | | | Yes | | Yes |
| Time fixed effects | | | | | | | | Yes | | Yes |
| Adjusted R-squared | 0.28 | 0.31 | 0.77 | 0.71 | 0.77 | 0.83 | 0.84 | 0.93 | 0.84 | 0.93 |
| No. of observations | 140 | 140 | 140 | 91 | 140 | 140 | 140 | 140 | 140 | 140 |

This Table reports the regression results for the model, $Systematic\ Component_{i,t} = \alpha + \beta_1 SovExp_{i,t} + \beta_2 VIX_t + \beta_3 Ccredit_{j,t} + \beta_4 SovExp_{i,t} * Ccredit_{j,t} + \beta_5 SovExp_{i,t} * Bcredit_{i,t} + \sum_j \theta_j C_j + \varepsilon_{i,t}$. The dependent variable is systematic component of bank default risk, namely $\beta_i * \lambda_{i,t}$. As control variables, Ccredit is a proxy for sovereign risk, measured as the 5-year sovereign CDS spread and VIX is a proxy for market risk aversion. The variable of interest SovExp is a bank's holdings of sovereign bonds divided by its total equity. $SovExp^{\perp Gamma}$ is the parts of SovExp that are orthogonal to Gamma--bank idiosyncratic default intensity. EZ is a dummy variable equal to 1 if a bank is in Eurozone. Bcredit represents bank risk, measured as the 5-year bank CDS spread. C_j represents a dummy for country j in our sample. ***, ** and * denote significance at the 1% , 5% and 10% level. t-values have been computed with White period standard errors and p-values are reported in parentheses below the coefficient estimates.

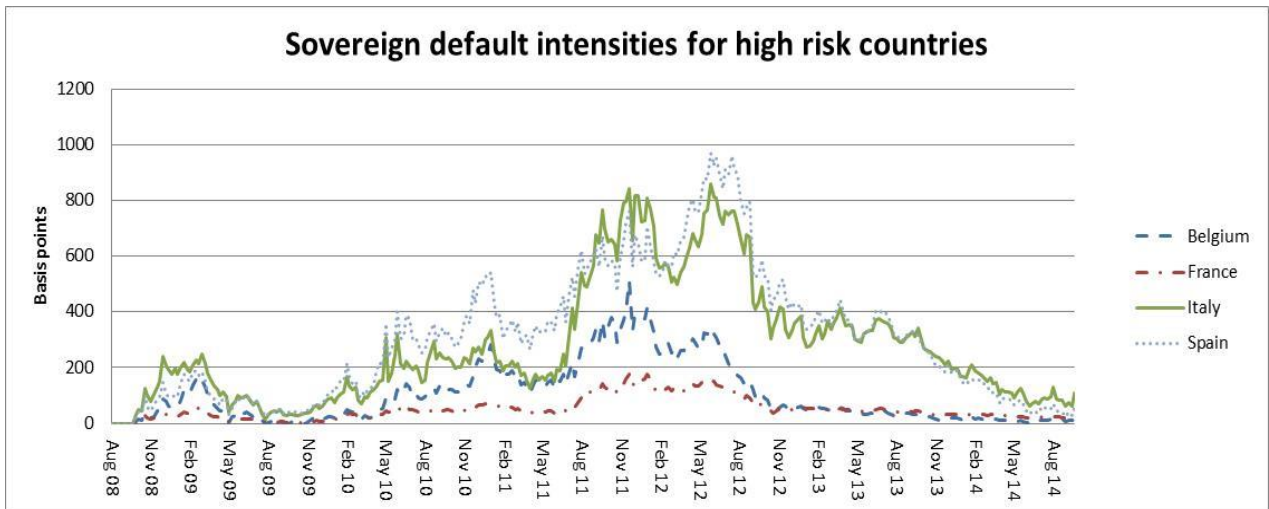


Figure 1.A Sovereign default intensities for high risk countries.

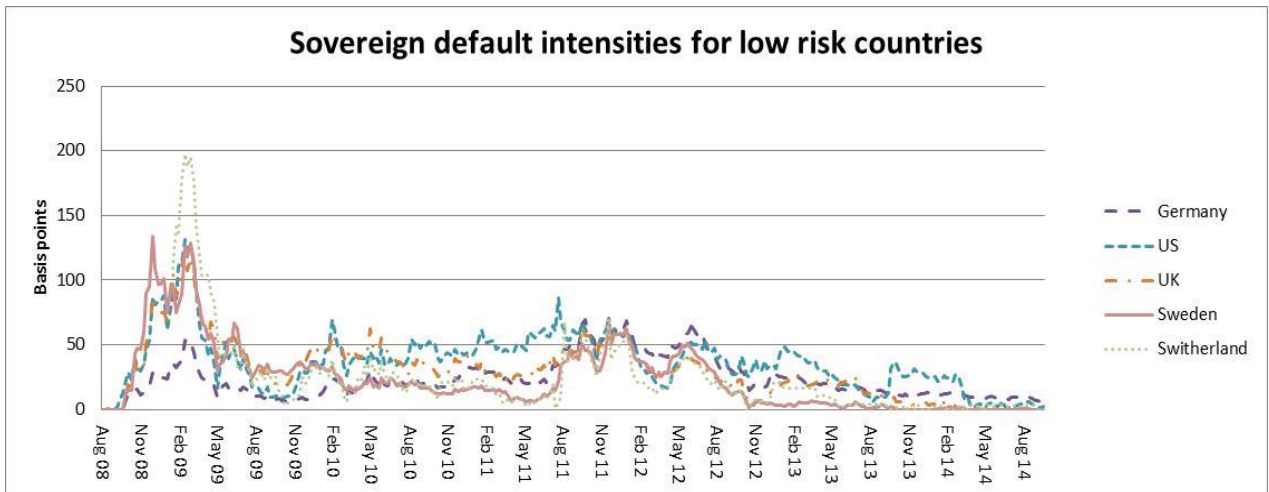


Figure 1.B Sovereign default intensities for low risk countries.

Figure 1. Sovereign default intensity

This Figure plots the time series of the risk-neutral default intensities estimated with a multifactor affine model for each country in the sample during the period August 2008 to September 2014.

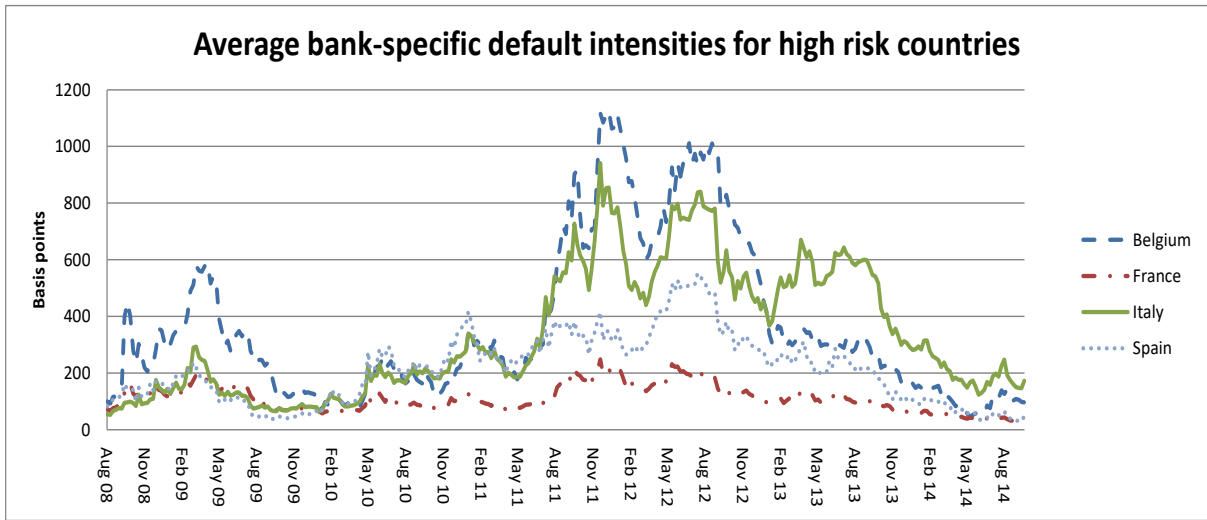


Figure 2.A Average default intensities across banks in high risk countries.

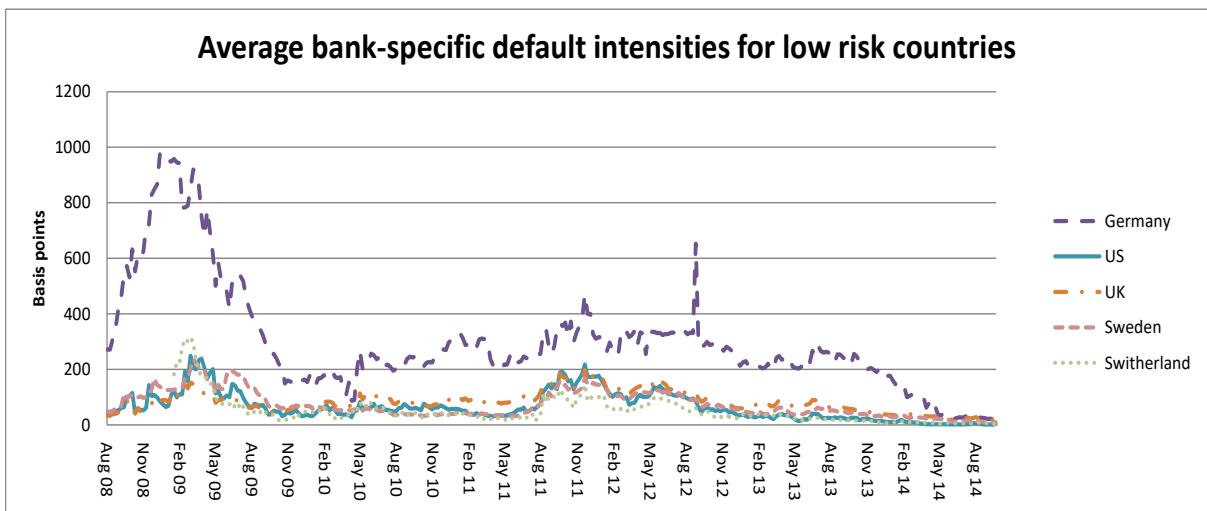


Figure 2.B Average default intensities across banks in low risk countries.

Figure 2. Bank-specific default intensity

This Figure plots the time series of the average risk-neutral bank-specific default intensity across banks in each country. Bank-specific default intensities are estimated with a multifactor affine model during the period August 2008 to September 2014.

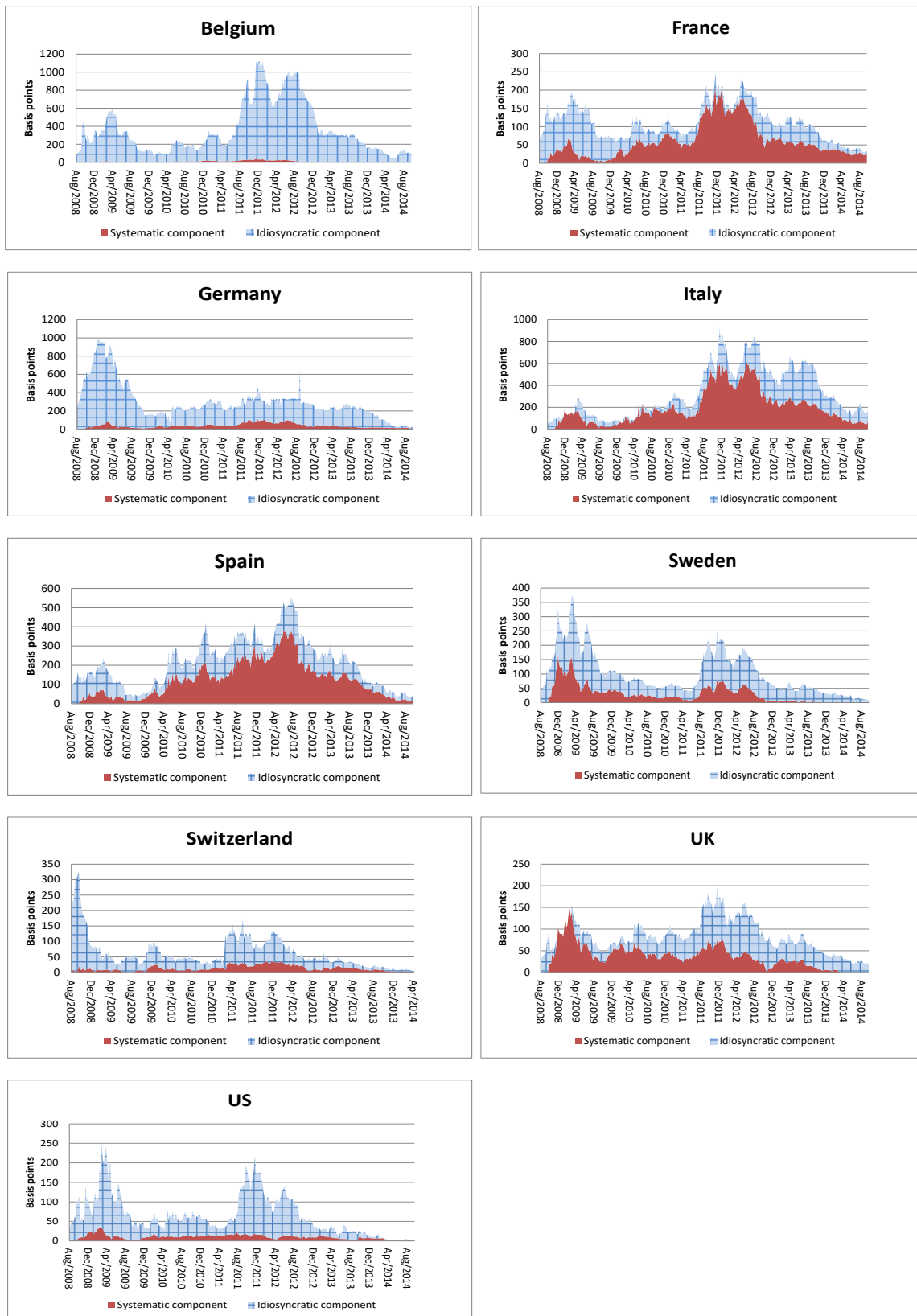


Figure 3. Default risk decomposition.

For each country in our sample, the red area represents the average systematic component of default risk ($\beta_i \lambda_t$) across all banks in the country and the blue checked area is the average idiosyncratic component (γ_{it}).

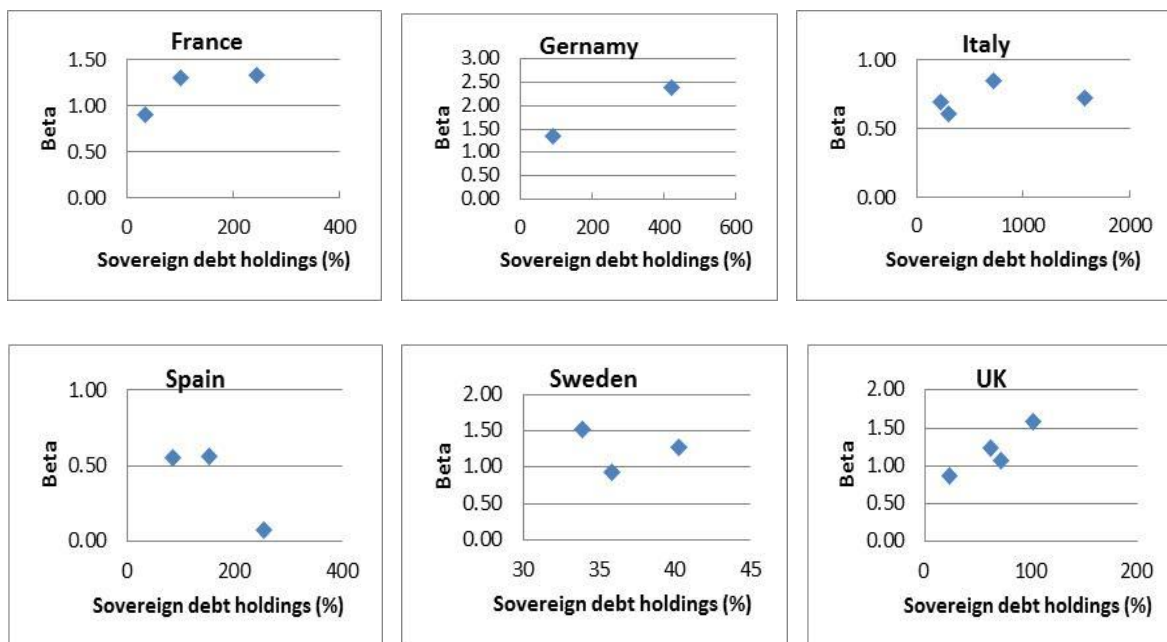


Figure 4. Beta and sovereign debt holdings. This Figure displays the scatterplot of banks' Betas (estimated from CDS spreads during the period 2008 to 2014) against the banks' average sovereign holdings to equity ratios. The ratios are averaged across 7 snapshots shown in reports published by the European Banking Authority between 2010 and 2013.

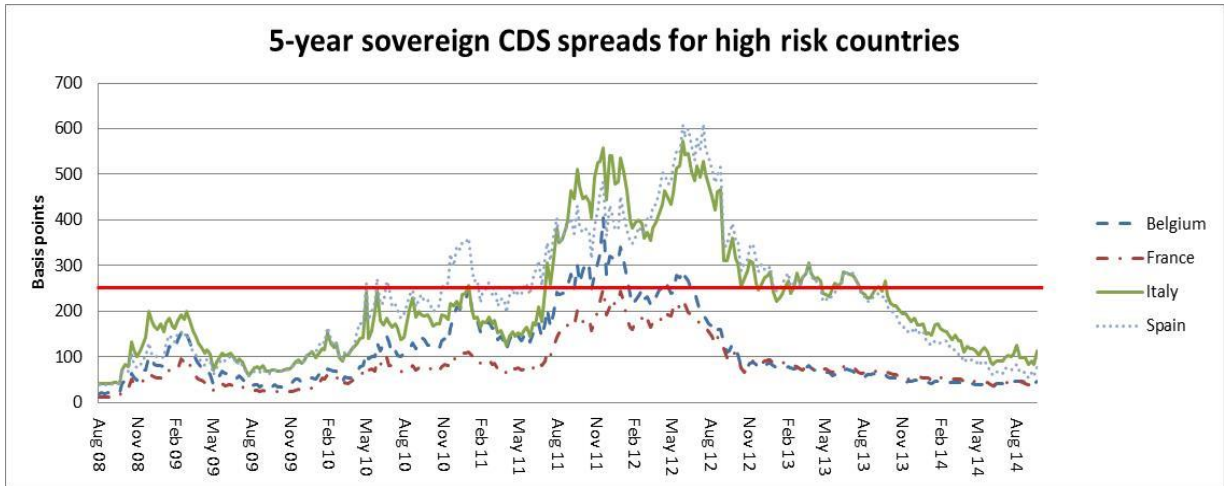


Figure 5.A 5-year sovereign CDS spreads for high risk countries.

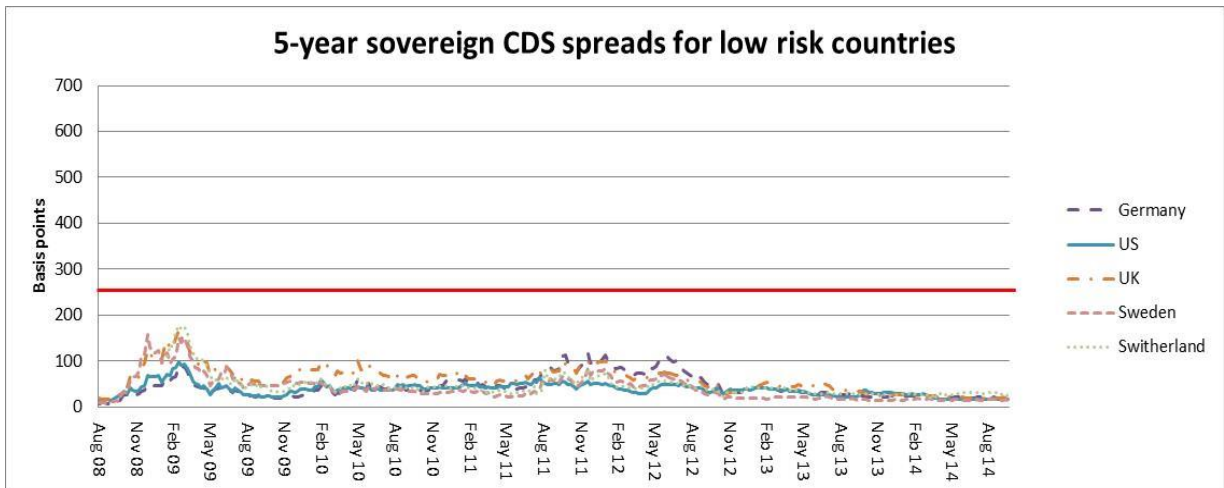


Figure 5.B 5-year sovereign CDS spreads for low risk countries.

Figure 5. Five-year sovereign CDS spreads

This Figure plots the time series of the 5-year CDS spreads for each country in our sample during the period 2008 to 2014.