Credit risk "Beta": the systematic aspect of bank default risk

Lei Zhao[1]
ICMA Centre, Henley Business School

This version: 2 June 2015

Abstract

Using information in US and European bank and sovereign CDS spreads we study the systematic component of banks' credit risk that stems from banks' common exposure to sovereign default risk. Based on a default intensity model, we find that sovereign default risk is a significant factor of bank default risk. During the period 2008-2014, on average US banks are much less sensitive to sovereign risk than their European counterparts. Within Europe the systematic component accounts for quite different proportions of the total bank default risk across countries. We also empirically confirm the asset holdings channel of the risk contagion theory by showing that a bank's credit risk Beta (a bank's sensitivity to sovereign risk) estimated with our model is positively related to its holdings of sovereign debt. Our findings have policy implications with respect to financial stability.

JEL Classification: G01, G12, G21, G28

Keywords: Banking/Financial intermediation, financial crisis, credit default swap, sovereign risk

[1] Contact email: l.zhao@icmacentre.ac.uk and irvingzhao@gmail.com

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 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 the 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. The most obvious and intuitive one is the fact that sovereign credit strength is perceived as the ceiling of corporate (including banks) credit strength, which is 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, namely the balance sheet hit channel investigated in Acharya et al. (2014). This channel contributes to the so called "diabolic loop" between banking and sovereign risk described in Brunnermeier et al. (2011). As sovereign risk increases, the asset side of banks' balance sheet is eroded due to the decreased value of their sovereign debt holdings. On top of that, sovereign risk can play a role in pushing up bank risk when the value of collateral that banks hold in the form of sovereign bonds decreases, which is called the collateral channel of risk transfer. The forth channel is through 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 Drechsler et al. (2013) or financial repression as documented in Becker and Ivashina (2014) and Reinhart and Rogoff (2011). 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 may be impaired when sovereign credit conditions weaken (see Zhao, 2015). 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 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 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 also identifies determinants of bank credit risk, which could address 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 sovereign to banks works through the government bonds held by local banks.

Adopting a 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 proposed by 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, 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 US is less fragile to a "Greek style" crisis, compared with 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.

In addition, we decompose a bank's total default risk into its systematic and idiosyncratic components. The systematic part is the product of a bank's c-Beta and the sovereign default intensity. We show that during a sovereign debt crisis, the systematic component, which represents the risk "transferred" from the sovereign to the 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 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 the sovereign debt crisis.

Finally, among other factors, a bank's holdings of domestic sovereign debt should increase its c-Beta, namely its sensitivity to sovereign risk. 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 the c-Beta we extracted from CDS spreads is positively related to the sovereign debt that banks hold in their 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 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 the Pan and Singleton (2008) model, Longstaff et al. (2011) decompose sovereign credit risk into a default-related component and a risk-premium component and investigate

[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 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. In contract, we focus on bank CDS spreads and apply a reduced-form model to decompose bank credit risk into a systematic component and an idiosyncratic component. In addition, 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 approach shows that the interconnections are not symmetric and sovereigns have more influence on banks and insurers than the other way around. Exploring excess correlation, which is 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. With 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. Therefore, they argue that the transfer of sovereign credit risk to banks operates through the expected government support to banks. 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. To support this argument, they find evidence that the connection is weakened by strong property rights institutions, which constrain the ability of the government to expropriate the private sector. Focusing on the other half of the risk transmission loop, Dieckmann and Plank (2012) find evidence of a private-to-public risk transfer, the extent of which 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. Indeed, Zhao (2015) documents evidence showing that higher implicit government guarantees extended to the financial sector lead to higher sovereign default risk due to the substantial impact that bailouts can have on public finances. 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 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 the CDS spread.

2.1 Modelling bank CDS spreads with a systematic component

To model CDS spreads, we adopt a framework that was first introduced by Duffie and Singleton (2003) and 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 its banks. More specifically, the model defines two independent types of credit events to trigger bank defaults. The first one is an idiosyncratic (bank-specific) shock that leads to the default of an individual bank. The second is a systematic one that may have ramifications for all banks 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 it is constant during our sample period. It is reasonable to view sovereign risk as the systematic risk for each bank in a country, since a country's default almost certainly will lead to systematic shock waves throughout the credit markets.[3] For each country, we normalize the sensitivity of the sovereign risk to the latent systematic risk to be one and as a result the β_i for each bank in the country can be treated as relative systematic risk sensitivity. Naturally, we interpret the β_i as a bank's credit risk sensitivity to the sovereign default, that is c-Beta.

[3] We use sovereign risk and systematic risk interchangeably hereafter.

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:[4]

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

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

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 on. In contrast to a bank, we model sovereign credit risk with a standard univariate default model such as the one applied in Pan and Singleton (2008). Consequently, for the sovereign there is only one source of shock and default occurs the first time there is an arrival of the sovereign Poisson process.

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

[4] 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.

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.[5]

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 ($\mathrm{b_i}$) can be derived. After suppressing the subscript t on λ_t and γ_{it} for notational simplicity, we have:

$$\mathrm{b_i} = \frac{(1-\mathrm{R_b})\int_0^{\mathrm{T}} \mathrm{D_t}\big(\mathrm{A}(\lambda,\mathrm{t})\mathrm{C}(\gamma_\mathrm{i},\mathrm{t}) + \beta_\mathrm{i}\mathrm{B}(\gamma_\mathrm{i},\mathrm{t})\mathrm{F}(\lambda,\mathrm{t})\big)\mathrm{dt}}{\int_0^{\mathrm{T}} \mathrm{D_t}\mathrm{A}(\lambda,\mathrm{t})\mathrm{B}(\gamma_\mathrm{i},\mathrm{t})\mathrm{dt}} \tag{3}$$

and similarly the CDS spread for sovereigns ($\mathrm{s_i}$) can be modelled as,

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

where $\mathrm{R_b}$ and $\mathrm{R_s}$ are recovery rates for banks and sovereigns respectively. $\mathrm{D_t}$ 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: $D(t) = E[exp\left(-\int_0^t r_t dt\right)]$, where r_t is the risk-free rate and we assume it is independent of the intensity processes λ_t and $\gamma_{\mathrm{i,t}}$. $\mathrm{A}(\lambda,\mathrm{t})$ and $\mathrm{F}(\lambda,\mathrm{t})$ are functions of λ and t and $\mathrm{C}(\gamma_\mathrm{i},\mathrm{t})$ and $\mathrm{B}(\gamma_\mathrm{i},\mathrm{t})$ are functions of γ_i and t. For semplicity we suppress the subscript i on γ_i,$\mathrm{a_i}$, $\mathrm{b_i}$ and $\mathrm{c_i}$. Then,

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

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

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

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

[5] See Ang and Longstaff (2013) for more details.

Where

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

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

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

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

And,

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

Detailed derivations are in the Appendix. With these closed-form solutions, we will be 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 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 [not sure that the 5 year is the most liquid sovereign CDS, you can double check this with Andrei in case the examiners ask you this question]. We use three-year, five-year and seven-year swap rates as the risk-free discount factor in Equation (3) and (4).[6] 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

[6] When calculating D_t on a particular day t I 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.

historical average recovery rates on senior corporate bonds reported by Moody's (see Moody's Investors Service, 2012c A 2015 annual report is now available and it covers the whole of 2014) and also ex-ante measures of LGD in Black et al. (2013).[7]

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:

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

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:

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

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

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, 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 objective function (9) that we want to minimize by summing up the squared distances. 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

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

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.[8] 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 in Europe. We collect weekly CMA London prices of CDS contracts for both banks and sovereigns.[9] 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,

[8] 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.

[9] 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.

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.

As pointed out by Ang and Longstaff (2013), the negative speed of mean reversion (parameter b and f) for many banks and sovereigns 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.

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, namely bank credit risk Beta, following which aggregate c-Beta (c-Beta at the country level) is calculated and analysed. Next, we focus on the systematic component of a bank's default risk. Finally, using data released by the EBA, we examine one of the risk transmission channels between a sovereign and its banks through the relationship between banks' c-Beta and their holdings of sovereign debt.

4.1 Risk-neutral default intensities for sovereigns and banks

4.1.1 Sovereign default intensity

We plot the time series of the default intensity of the sovereign Poisson process λ_t for each country in Figure 1. We divide countries in our sample 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.[10] 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 and European countries outside the Euro area and Germany. As shown in Figure 1, in general, sovereign default intensities move in the same direction. This is consistent with the findings in Longstaff et al. (2011) and also 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. We 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 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. Approximately, those values of default intensity are equivalent to a one-year risk-neutral probability of default of $1 - \exp(-0.095) = 0.091$

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

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 group seem to behave differently from Belgium and France during the following European debt crisis. If we look at 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 seems that the European sovereign debt crisis has much less impact on the default prospects of low risk countries, compared with the 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 the 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 peak 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 county. Form next section, we focus on the systematic component of bank default risk $\beta_i \lambda_t$ and we start with the Beta, the key parameter in the paper.

4.2 Bank credit risk 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 the information in the CDS market, we summarize such sovereign risk sensitivity with our credit risk Beta. Table 2 contains the estimated c-Beta and the standard errors for each bank in the sample. The 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, Spain's Caixabank, whose c-Beta is only 0.076, has little sensitivity 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 the 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 ("financial repression"), among other channels. 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 derivatives, 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. The magnitude of c-Beta may have policy implications. On one hand, high c-Beta banks should be encouraged to reduce their exposure to sovereign debt. One possible solution is to adjust the risk weight of sovereign bonds according 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 bonds held by banks as in Basel III, bank-specific risk weight related to c-Beta could provide the right incentive for banks to manage their risk. On the other hand, governments should take into consideration banks' c-Beta, namely banks' capacity to take more sovereign exposure, when they "need" to exercise financial repression for the broader interest.

4.3 c-Beta at country level

We also look at the aggregate 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-Betas across all banks in a country. Table 3 shows that the aggregate c-Beta is quite different both across regions and also across countries. If comparing the US with Europe, aggregate c-Beta in the US is around one quarter of that in Europe, which may indicate that sovereign risk in the US is much less a concern for banks than in Europe. Within Europe, interestingly, countries like Germany and Switzerland, which have been perceived to be relatively safe during the sample period, have quite high c-Beta. As documented in the next sub-Section, the systematic component as a whole, namely the product of c-Beta and sovereign default intensity, is quite low for these countries as expected. Combined with the fact that the c-Beta is relatively high, the low systematic component is largely due to the low sovereign risk in these countries. Our findings suggest that the banks in these safe countries may be more fragile to sovereign risk than their counterparts in riskier countries. In other words, banks in Germany may suffer much more than banks in Italy if Germany becomes as risky as Italy. The 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 could be that countries with higher aggregate c-Beta are more motivated to keep the probability of public default low due to the concern of post-default declines in private credit caused by increased default risk of their banking system. This argument is consistent with the findings in Gennaioli et al. (2014). The policy implication is that, compared with low c-Beta countries, it is more important for high c-Beta countries to keep their credit healthy so that their banking system will not be disturbed and the probability of a financial crisis will remain low.

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 the 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 actually 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. 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, the credit risk Beta depends on several factors, such as 1) a bank's holdings of sovereign debt, 2) the potential pressure a country can exert on a bank to buy more sovereign debt during a crisis and 3) a bank's risk management strategy regarding sovereign debt. Some of the above can be too subtle to measure accurately and unfortunately we do not possess the data to capture the last two factors.[11] Nevertheless, data regarding bank holdings of local government debt are available from the EBA. Therefore, we are able to investigate the relationship between our c-Beta and the first factor. A positive relationship between them can also corroborate our previous finding that the c-Beta is a measure of bank credit sensitivity to sovereign risk.[12] Specifically, we collect data of bank holdings of sovereign debt 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 banks out of our 25 European banks and covers the period between March 2010 and December 2013, with 7 snapshots in total. Figure 4 reveals the first impression of a positive relationship between our c-Beta and a bank's 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:

[11] One 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.

[12] 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 its banks, instead of providing a complete picture of the risk transmission mechanism.

$$Systematic\ Component_{i,t} = \alpha + \beta_1 SovExp_{i,t} + \beta_2 VIX_t + \beta_3 Ccredit_{j,t} + \beta_4 SovExp_{i,t} * Ccredit_{j,t} + \beta_5 SovExp_{i,t} * Bcredit_{i,t} + \sum_j \theta_j C_j + \varepsilon_{i,t} \quad (11)$$

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 credit risk Beta and sovereign default risk, namely $\beta_i \lambda_t$. SovExp is the variable of interest, which is measured as bank holdings of sovereign debt divided by a bank's total equity. VIX and Ccredit are included as control variables. We use the 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 represents a dummy 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 in Equation (7). 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 $SovExp_{i,t} * Bcredit_{i,t}$ 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).[13] 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 have larger sensitivity 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 a part of the whole systematic component $\beta_i\lambda_t$, and SovExp.[14] Therefore, we need to control for the other part of the component, which is 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. 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. The results in column 4 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

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

[14] 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.

differently, there might be a "wake-up call" that activates the relationship between c-Beta and sovereign debt holdings. To examine it, we introduce the interaction term between SovExp and Ccredit in column 5. 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 5 and it is 6.252/0.024=261 as specified in column 6). 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". We investigate the interaction term SovExp*Bcredit instead of SovExp*Ccredit in column 7 and 8. 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 (15.832/0.032=495 in column 7 and 9.203/0.022=418 in column 8, 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 regression results are contained in column 6 and 8 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 carried by sovereign bonds since Basel I in 1988. However, a further 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 4 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 5 through 8 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 relatively developed countries in Europe, their debt can become rather risky and the sovereign risk can be transmitted to the banking system easily and quickly. A practical measure of bank's sensitivity to sovereign risk, such as the c-Beta proposed in the 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 sovereign 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 some policy implications. First, banks with high c-Beta should be encouraged to reduce their exposure to sovereign debt, such as reducing their holdings of sovereign debt or through hedging. Second, 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, namely the magnitude of their c-Beta.

Obviously, much future work is needed to investigate the driven factors, other than domestic sovereign debt holdings, that determine the value of a bank's c-Beta. For example, as argued in Gennaioli et al. (2014), a more developed financial system may make banks more vulnerable to sovereign default. It would be interesting to empirically test their theory with our measure of bank vulnerability. A positive relationship between a bank's c-Beta and the importance of investor rights and corporate governance in its home country would be expected. Furthermore, a bank's default risk may not only be sensitive to its home country's default risk as investigated in the paper, it may also be influenced by the credit risk of other countries. The inter-country risk transfer operates through a bank's direct holdings of oversea sovereign bonds. Another channel works through the mutual holdings of sovereign debt by countries. For example, as the credit risk of Greece increases, the default risk of Germany increases accordingly since Germany holds Greek debt in its balance sheet. This in turn increases the default risk in the German banking system through the risk transmission mechanism we discuss in this paper. Our work could be further developed by investigating such cross-border risk transfer from a country to foreign banks.

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.[15]

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:

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

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

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

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

$$PreLeg = ProLeg \tag{A.3}$$

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:

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

$ProLeg =$

$(1-R)D(t)E\left[exp\left(-\int_0^t \beta\lambda_s ds\right)\right]E\left[\gamma_t exp\left(-\int_0^t \gamma_s ds\right)\right]+$

$$\beta E\left[exp\left(-\int_0^t \gamma_s ds\right)\right]E\left[\lambda_t exp\left(-\int_0^t \beta\lambda_s ds\right)\right] \qquad (A.4)$$

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):

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

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 $A_1(0)=0\ and\ A_2(0)=0$.

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 $B_1(\mathrm{t})\exp(B_2(t)\gamma)$, 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 $(F_1(\mathrm{t}) + F_2(\mathrm{t})\lambda)\exp(A_2(t)\lambda)$, we can substitute it into the PDE. It can be shown that the following two Riccati equations should be satisfied:

$$F_2' = (e + \sigma^2)A_2F_2 - \mathrm{f}F_2,$$

$$F_1' = eF_2 + \mathrm{e}F_1A_2,$$

subject to the initial conditions $F_1(0) = 0 \; and \; F_2(0) = 0$. 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 $(C_1(\mathrm{t}) + C_2(\mathrm{t})\gamma)\exp(B_2(t)\gamma)$, the same procedure can be used to derive $C_1(t)$ and $C_2(t)$ in Equation (7).

References

Acharya, V.V., Drechsler, I., Schnabl, P., 2014. A pyrrhic victory? Bank bailouts and sovereign credit risk. Journal of Finance 69, 2689-2739.

Acharya, V.V., Eisert, T., Eufinger, C., Hirsch, C., 2014. Real effects of the sovereign debt crisis in Europe: Evidence from syndicated loans. CEPR Discussion Paper No. DP10108.

Alter, A., Beyer, A., 2014. The dynamics of spillover effects during the European sovereign debt turmoil. Journal of Banking and Finance 42, 134-153.

Altman, E. I., 1992. Revisiting the high-yield bond market. Financial Management 21, 78-92.

Ang, A., Longstaff, F.A., 2013. Systemic sovereign credit risk: Lessons from the U.S. and Europe. Journal of Monetary Economics 60, 493-510.

Bai, J., Wei, S.J., 2012. When is there a strong transfer risk from the sovereigns to the corporates? Property rights gaps and CDS spreads. Federal Reserve Bank of New York Staff Report No. 579.

Becker, B., Ivashina, V., 2014. Financial repression in the European sovereign debt crisis. Swedish House of Finance Research Paper No. 14-13.

Berndt, A., Douglas, R., Duffie, D., Ferguson, M., Schranzk, D., 2004. Measuring default risk premia from default swap rates and EDFs. BIS Working Paper No. 173.

Billio, M., Getmansky, M., Gray, D., Lo, A.W., Merton, R.C., Pelizzon, L., 2013. Sovereign, bank and insurance credit spreads: Connectedness and system networks. MIT Working Paper.

Black, L., Correa, R., Huang, X., Zhou, H., 2013. The systemic risk of European banks during the financial and sovereign debt crises. International Finance Discussion Paper No. 1083.

Black, F., Cox, J.C., 1976. Valuing corporate securities: Some effects of bond indenture provisions. Journal of Finance 31, 351-367.

Brunnermeier, M. K., Garicano, L., Lane, P. R., Pagano, M., Reis, R., Santos, T., Thesmar, D., Van Nieuwerburgh, S., Vayanos, D., 2011. European Safe Bonds: ESBies. Euro-nomics.com.

Correa, R., Lee, K.H., Sapriza, H., 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.

Cox, J.C., Ingersoll, J.E., Ross, S.A., 1985. A theory of the term structure of interest rates. Econometrica 53, 385-407.

Das, S.R., Sundaram, R.K., 2000. A discrete-time approach to arbitrage-free pricing of credit derivatives. Management Science 46, 46-62.

De Bruyckere, V., Gerhardt, M., Schepens, G., Vennet, R.V., 2013. Bank/sovereign risk spillovers in the European debt crisis. Journal of Banking and Finance 37, 4793-4809.

Dieckmann, S., Plank, T., 2012. Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. Review of Finance 16, 903-934.

Drechsler, I., Drechsel, T., Marques-Ibanez, D., Schnabl, P., 2013. Who borrows from the Lender of Last Resort? Working Paper.

Duffie, D., 1998. Defaultable term structure models with fractional recovery of par. Working Paper.

Duffie, D., 1999. Credit swap valuation. Financial Analysts Journal 57, 76-87.

Duffie, D., Singleton, K.J., 1999. Modeling term structures of defaultable bounds. Review of Financial Studies 12, 687-720.

Duffie, D., Pan, J., Singleton, K.J., 2000. Transform analysis and asset pricing for affine jump-diffusions. Econometrica 68, 1343-1376.

Duffie, D., Pedersen, L.H., Singleton, K.J., 2003. Modeling sovereign yield spreads: A case study of Russian debt. Journal of Finance 58, 119-159.

Duffie, D., Singleton, K.J., 2003. Credit risk. Princeton University Press, Princeton, NJ.

Franks, J.R., Torous, W., 1994. A comparison of financial recontracting in distressed exchanges and Chapter 11 reorganizations. Journal of Financial Economics 35, 349-370.

Gennaioli, N., Martin, A., Rossi, S., 2014. Sovereign default, domestic banks, and financial institutions. Journal of Finance 69, 819-866.

Houweling, P., Vorst, T., 2005. Pricing default swaps: Empirical evidence. Journal of International Money and Finance 24, 1200-1225.

Hull, J., Predescu, M., White, A., 2004. The relationship between credit default swap spreads, bond yields, and credit rating announcements. Journal of Banking and Finance 28, 2789-2811.

Jarrow, R.A, Turnbull, S.M., 1995. Pricing derivatives on financial securities subject to credit risk. Journal of Finance 50, 53-85.

Lando, D., 1998. On Cox processes and credit risky securities. Review of Derivatives Research 2, 99-120.

Leonello, A., 2014. Government guarantees and the two-way feedback between banking and sovereign debt crises. Working Paper.

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 5, 2213-2253.

Longstaff, F.A., Pan, J., Pedersen, L.H., Singleton, K.J., 2011. How sovereign is sovereign credit risk? American Economic Journal: Macroeconomics 3, 75-103.

Mayordomo, S., Peña, J.I., Schwartz, E.S., 2014. Are all credit default swap databases equal? European Financial Management 20, 677-713.

Merton, R.C., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29, 449-470.

Moody's Investors Service, 2012a. Rating action: Moody's downgrades Spain's government bond rating to Baa3 from A3, on review for further downgrade.

Moody's Investors Service, 2012b. Rating action: Moody's downgrades Spanish banks.

Moody's Investors Service, 2012c. Corporate default and recovery rates, 1920-2012.

Pagano, M.S., Sedunov, J., 2014. What is the relation between systemic risk exposure and sovereign debt? Working Paper.

Pan, J., Singleton, K.J., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads. Journal of Finance 63, 2345-2384.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22, 435-480.

Reinhart, C.M., Rogoff, K.S., 2011. From financial crash to debt crisis. American Economic Review 101, 1676-1706.

Weiß, G., Bostandzic, D., Neumann, S., 2014. What factors drive systemic risk during international financial crises? Journal of Banking and Finance 41, 78-96.

Zhao, L., 2015. Implicit government guarantees in European financial institutions. Working Paper.

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	US
Aggregate c-Beta	0.082	1.167	1.572	0.720	0.399	1.243	1.570	1.185	1.010	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)
Constant	69.583***	-68.081***	-40.643***	-130.972***	-116.518***	-4.578	-40.272**	-3.755
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.870)	(0.015)	(0.895)
SovExp	18.708***	18.267***	5.942**	1.945**	-3.981	-6.252	-15.832*	-9.203
	(0.000)	(0.000)	(0.020)	(0.031)	(0.230)	(0.172)	(0.073)	(0.180)
VIX		7.585***	1.284	0.397	0.505		1.192**	
		(0.000)	(0.133)	(0.382)	(0.300)		(0.017)	
Ccredit			0.778***	0.906***	0.844***	0.791***	0.750***	0.802***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Country dummy				Yes	Yes		Yes	
SovExp*Ccredit					0.017**	0.024**		
					(0.039)	(0.031)		
SovExp*Bcredit							0.032**	0.022*
							(0.043)	(0.071)
Firm fixed effects						Yes		Yes
Time fixed effects						Yes		Yes
Adjusted R-squared	0.277	0.308	0.768	0.834	0.837	0.931	0.831	0.932
No. of observations	140	140	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. SovExp is a bank's holdings of sovereign bonds divided by its total equity. 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.

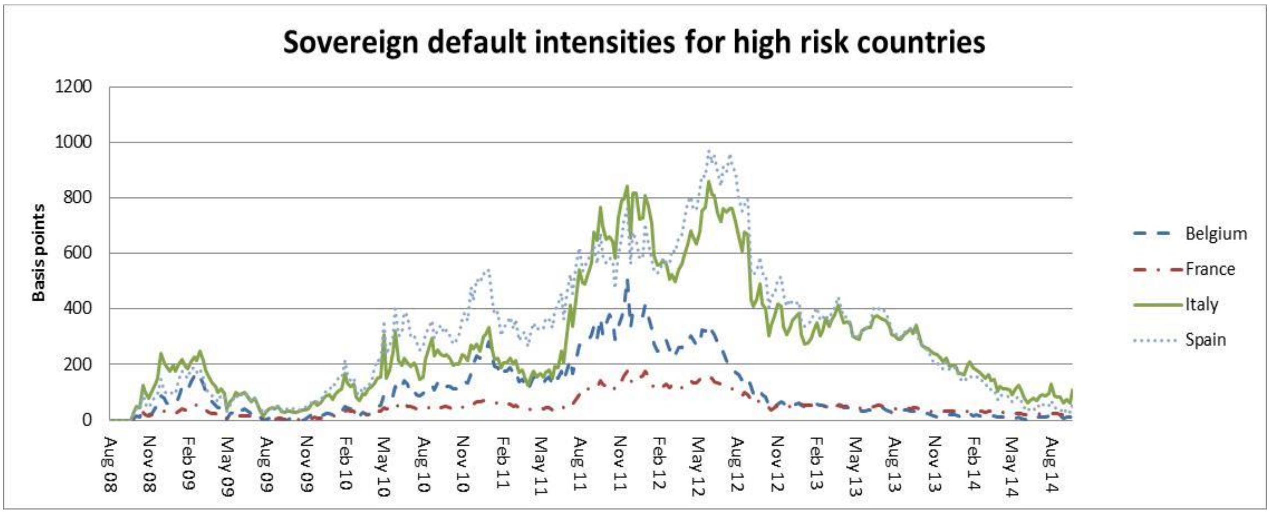

Figure 1.A Sovereign default intensities for high risk countries.

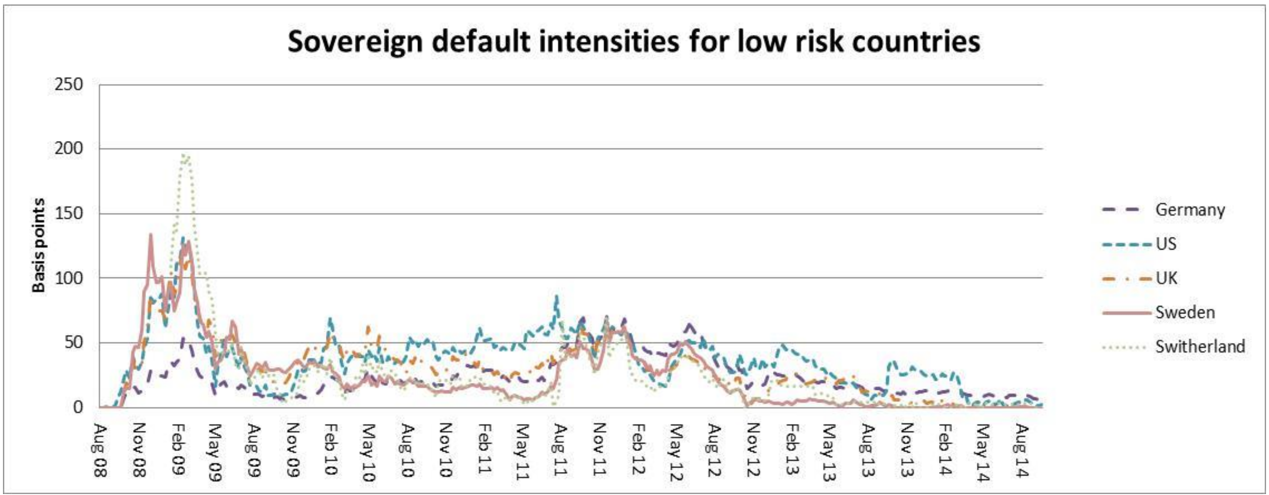

Figure 1.B Sovereign default intensities for low risk countries.

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.

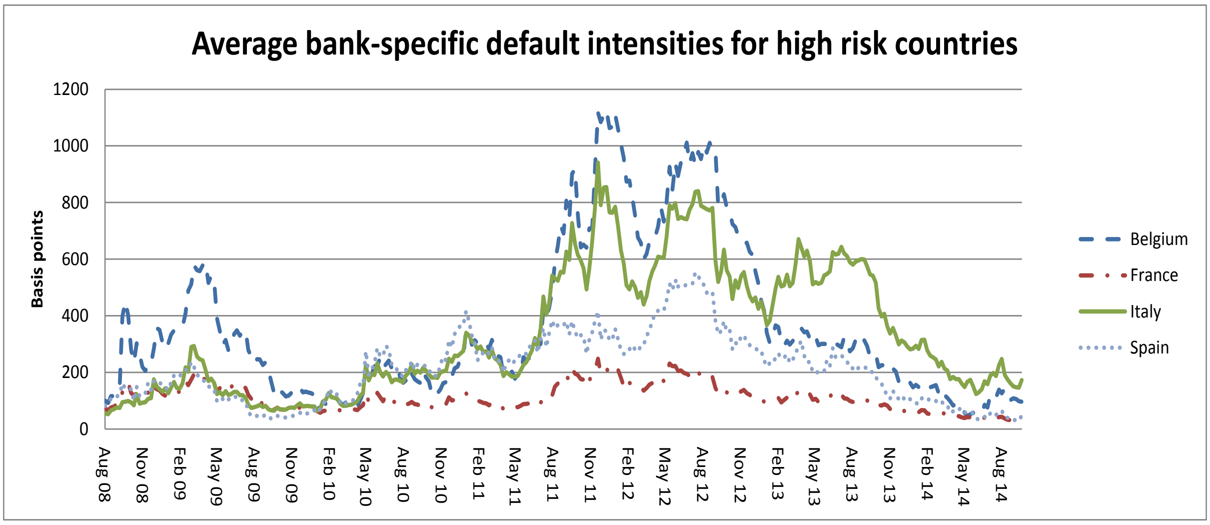

Figure 2.A Average default intensities across banks in high risk countries.

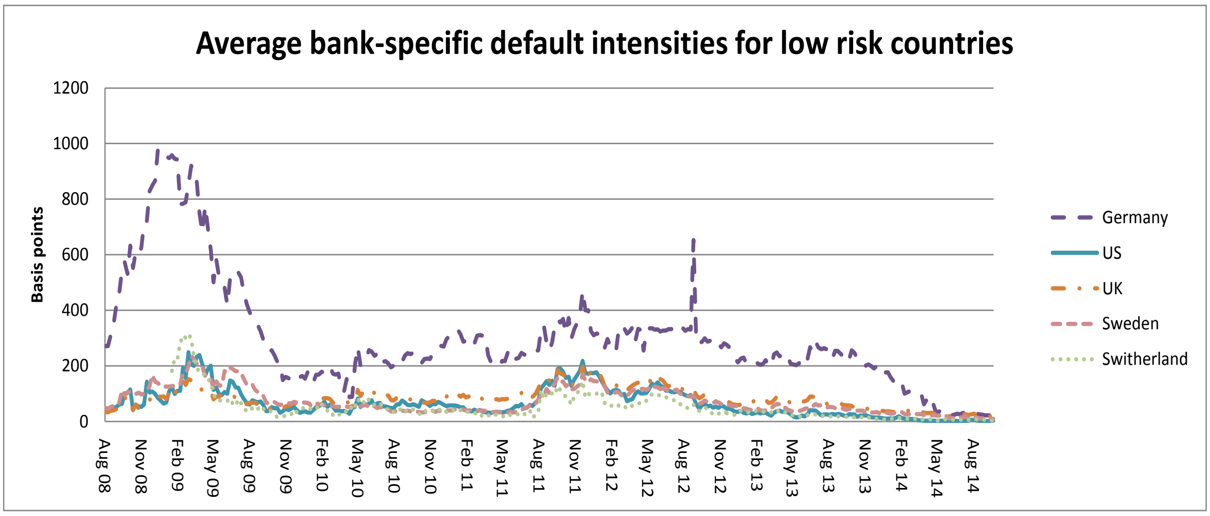

Figure 2.B Average default intensities across banks in low risk countries.

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.

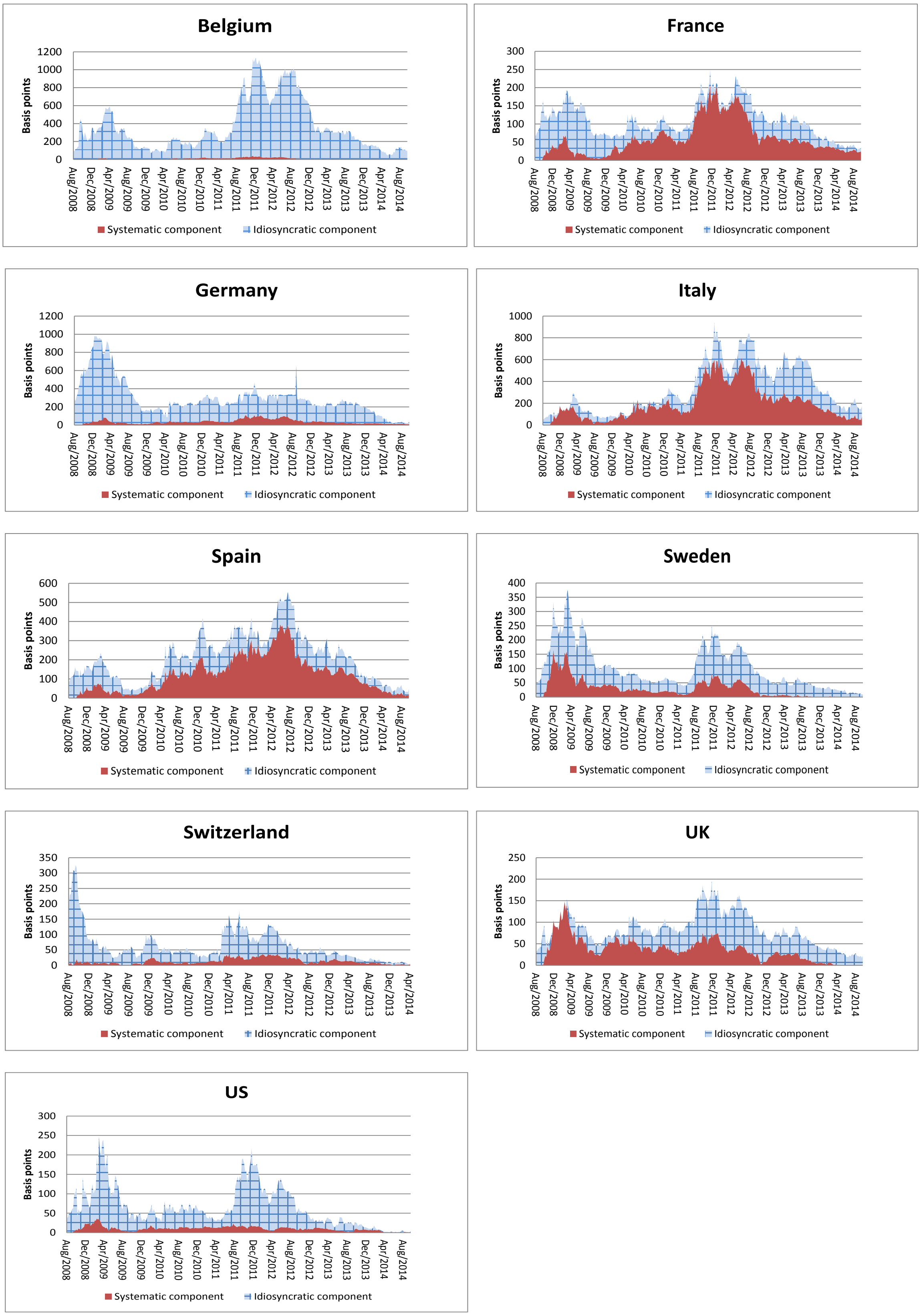

Figure 3. Default risk decomposition.

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}).

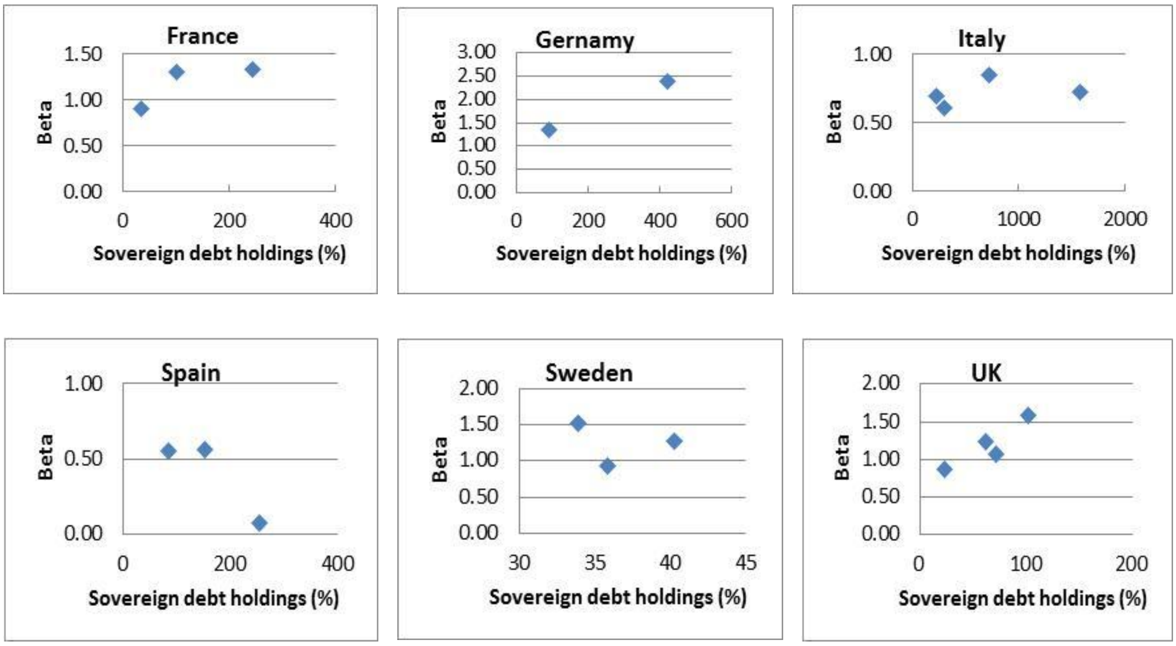

Figure 4. Beta and sovereign debt holdings. This Figure displays the scatterplot of banks' Betas (estimated from CDS spreads during the period 2008 to 2014) against the banks' average sovereign holdings to equity ratios. The ratios are averaged across 7 snapshots shown in reports published by the European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

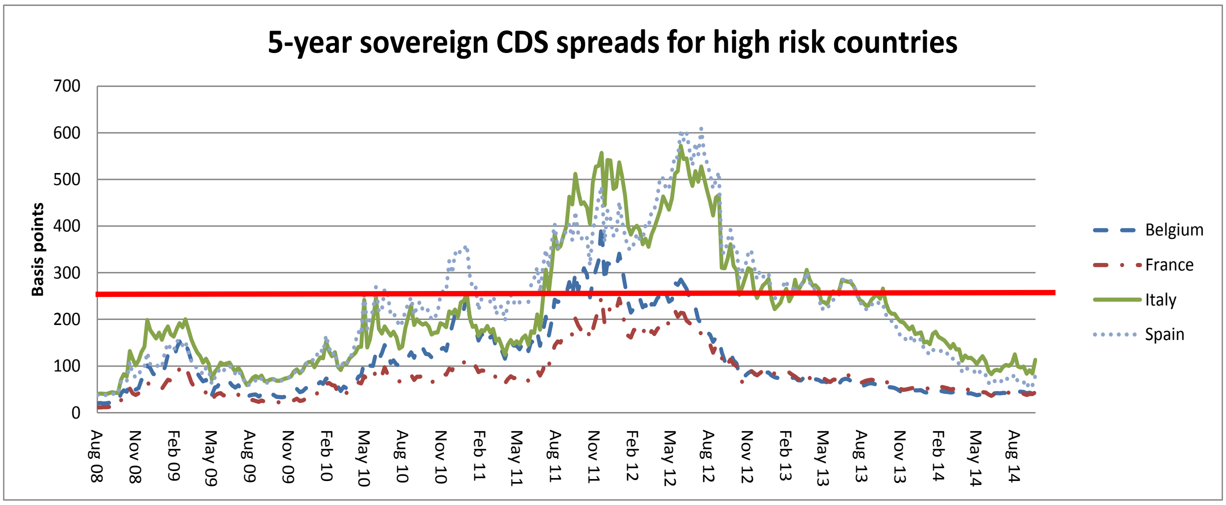

Figure 5.A 5-year sovereign CDS spreads for high risk countries.

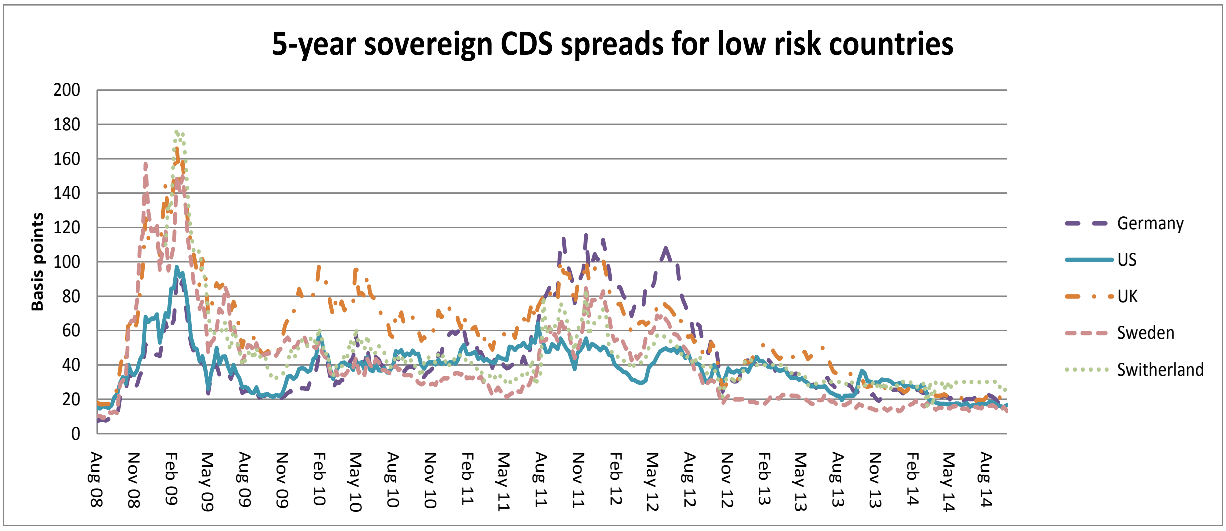

Figure 5.B 5-year sovereign CDS spreads for low risk countries.

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.