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ON BANK CREDIT RISK: SYSTEMIC OR BANK-SPECIFIC? EVIDENCE FROM THE US AND UK

by Junye Li* and Gabriele Zinna**

Abstract

We develop a multivariate credit risk model that accounts for joint defaults of banks and allows us to determine how much of banks' credit risk is systemic. We find that the US and the UK differ not only in the evolution of systemic risk, but also in their banks' systemic exposures. In both countries, however, systemic credit risk varies substantially over time, represents about half of total bank credit risk on average and leads to high risk premia. Furthermore, the results suggest that sovereign and bank systemic risk are closely interlinked in the UK.

JEL Classification: F34, G12, G15.
Keywords: systemic bank credit risk, credit default swaps, distress risk premia, Bayesian estimation.

Contents

1. Introduction 5
2. Pricing CDS and modeling default 10
3. The data 13
4. Model estimation 15
5. Systemic credit risk 20
6. Bank-specific credit risk 30
7. Distress risk premia 33
8. Concluding remarks 37
Appendix. 38
References 39
Tables and figures 45
Internet appendix 59

* ESSEC Business School.
** Bank of Italy, Economics, Statistics and Research.

1 Introduction

The recent financial crisis reveals that much work remains to better understand the sources of systemic risk and to improve our monitoring tools (Bernanke (2011)). During the 2008-13 period, banks' funding costs display a substantial degree of comovement (see Figure 1). The likelihood of a systemic event, resulting in a cascade of bank defaults, is possibly jointly determining banks' funding costs. And the probability of such systemic event taking place varies strongly over time, therefore exposing investors to unpredictable changes in systemic risk. However, there are significant differences in the level of banks' funding costs, suggesting that banks' exposures to such systemic event differ. Also, banks' credit default swap (CDS) premia are affected at different times, and to a different extent, so that the source of banks' credit risk is partly idiosyncratic. Taken together, these facts suggest that during a period of financial stress, bank credit risk displays complex dynamics. However, understanding the nature of bank credit risk is of fundamental importance, as failures of financial institutions can impose severe externalities on the rest of the economy (Acharya et al. (2010)). In order to contain this risk, national authorities have undertaken a number of measures. As a result, banks' credit risk and sovereign credit risk have become more intimately linked (Acharya, Drechsler, and Schnabl (2011)).

Our goal in this paper is to study systemic credit risk within the US banking system and contrast to that within the UK banking system. We do this by developing a multivariate credit model that allows for joint defaults of banks in conjunction with a systemic event (systemic risk). That is, systemic risk points to the shared vulnerability of banks to a common event. This common event could reflect the state of the domestic banking sector, or more generally the aggregate state of the economy, therefore inducing correlation among banks' credit risk. Further, the probability of such systemic event occurring can strongly vary over time. But in reality banks vary significantly in their business models and geographic footprint, and can therefore have different levels of systemic risk, i.e. different probabilities of default in the event of a systemic shock (systemic exposure). Banks' business models, however, can also be the cause of bank-specific vulnerabilities. For this reason, in the model banks' credit risk is also driven by a separate idiosyncratic component, which can in turn lead to individual bank defaults. In sum, banks can default either in conjunction with a systemic credit shock or with an idiosyncratic credit shock, and therefore banks' (total) credit risk can be decomposed into a systemic risk component and an idiosyncratic risk component.[1]

We estimate the model using the full cross-section of CDS term structure data for seven major US banks, and separately for seven major UK banks over the 2008-13 period. In addition to bank CDS data, we include in the estimation the term structure of sovereign CDS data. Precisely, in our baseline specification we assume that the sovereign can only default in conjunction with a systemic event. In this way, we can relate banks' systemic exposures to the exposure of the sovereign to the same systemic event. The inclusion of the sovereign in the estimation therefore allows us to shed new light on the link between sovereign and bank credit risk.

In this study, we refer to the probability of more than one bank defaulting simultaneously as systemic risk. A natural question is whether this is truly systemic risk or more simply systematic risk. In a similar framework to ours, joint default events have been defined either as systematic events (Feldhutter and Nielsen (2012)) or systemic events (Ang and Longstaff (2012)). Systematic risks are generally aggregate risks that cannot be avoided by diversification, for which investors want to be compensated. In contrast, systemic risk remains a poorly understood concept (Hansen (2013)).[2] That said, events that can lead to the breakdown or major dysfunction in financial markets are often denoted as systemic events. In our model, joint default events involve major banks and can therefore be highly dysfunctional for the financial system, imposing severe externalities for the rest of the economy.[3] In addition, the severity of such events is reflected in the possibility that the sovereign is also allowed to default in conjunction with joint defaults of banks. We therefore refer to these events as systemic.

A number of important results emerge from the empirical analysis. First, systemic credit risk displays a similar evolution in the US and UK, though there are also significant differences. Both the US and UK systemic bank credit risks reach their sample peaks in 2009, but the response of UK systemic risk to Lehman's default is more immediate and persistent than the US. Moreover, UK systemic risk strongly reacts to the start and consequent worsening of the Eurozone crisis. However, we find that major turning points in the US and UK systemic bank credit risk are associated with the same set of major political and financial events. That said,

[1] In this paper the words credit risk and default risk are used interchangeably.

[2] Systemic risk remains a poorly understood concept in that there is no "off-the-shelf" model to measure it. According to Hansen (2013), systemic risk is basically "a grab bag of scenarios that are supposed to rationalize intervention in financial markets (through macroprudential policies)."

[3] Financial distress can then impact the real economy through a number of channels, see for example He and Krishnamurty (2013), among others.

the intensity of the responses of the US and UK systemic risk to these events differs. We also find that the evolution of systemic credit risk in both the US and UK is strongly related to the evolution of financial variables. In particular, systemic credit risk increases significantly when corporate spreads and German CDS premia increase. In contrast, systemic risk decreases when the stock market and medium-term government bond yields increase. An increase in the Asian CDX spread is also associated with an increase in systemic risk. By contrast, when the Emerging Market CDX spread decreases, the US and UK systemic risks increase. This result is possibly consistent with the view that at times some emerging market economies have decoupled from advanced economies (Kose, Otrok, and Prasad (2012)).

Second, there is a dramatic variation across US banks in terms of their systemic exposures, whereas UK banks display systemic exposures of similar magnitude. In general, it is true that riskier banks (i.e. banks with higher CDS premia), in particular for the US, display higher probabilities of default in the event of a systemic crisis. For this reason, we construct an alternative measure of systemic risk that is comparable across banks of different riskiness. According to this metric, the ordering of systemic banks substantially changes. For example, although Wells Fargo has low probability of default in the event of a systemic crisis, the nature of its credit risk is largely systemic on average. However, there is strong variability in the fraction of systemic risk to total credit risk. We identify a group of high systemic risk US banks that consists of Wells Fargo, JP Morgan and Citigroup, and a separate group of low systemic risk banks that includes Bank of America, Goldman Sachs, Morgan Stanley and Capital One. Similar results hold for the UK banks in that the fraction of systemic credit risk is large and displays substantial time variation. Specifically, systemic risk explains a larger fraction of HSBC, Standard Chartered and Barclays' credit risk, whereas the type of credit risk of Royal Bank of Scotland, Lloyds Banking Group, Santander UK and Nationwide is mainly idiosyncratic. This grouping, to some extent, reflects the geographic footprint of UK banks. We then investigate what drives idiosyncratic bank credit risk by regressing idiosyncratic intensities on European stock market returns. We find that US and UK bank idiosyncratic credit risks are associated with changes in the Italian stock market. UK banks' idiosyncratic credit risk also increases with negative returns on the Greek stock market. But the magnitude of these effects strongly varies across banks.

Third, UK bank systemic exposures are about the same as the UK sovereign exposure, whereas US banks have on average three times larger systemic exposures than the US sovereign. This result may reflect the large size of the UK banking sector relative to the size of the UK economy, and therefore the higher UK sovereign's exposure to a systemic event. In addition, our measure of systemic bank credit risk strongly co-moves with UK sovereign risk over time. Taken together, these results show that, despite the US and UK sovereigns display similar levels of default risk, sovereign and bank systemic risk are more strongly linked in the UK. This result is also consistent with the fact that the estimated cost of bailouts is considerably higher for the UK than the US, 54 and 22 percent of GDP, respectively (Panetta et al. (2009)). We also find evidence that bank bailouts are associated with a fall of bank risk, largely captured by a fall in the bank-specific intensities for the UK.

Finally, we find that the systemic component of CDS spreads is largely driven by a high risk premium. This result, consistently with economic theory, suggests that investors demand a particularly high compensation for being exposed to rare but severe events such as joint defaults of large banks. By contrast, idiosyncratic default risk and default risk-premium contribute in about equal measure to the idiosyncratic component of CDS spreads for a number of banks. Moreover, the total risk premium component explains a large fraction of CDS spreads. Further, the US and UK banks' risk premia increase when the stock market declines and the five-year government bond yield rises. For a number of UK banks, increases in the risk premia are also associated with increases in the stock market volatility.

Ang and Longstaff (2013) develop a similar affine credit model for the cross-section of US States and European countries' CDS spreads. The novelty of our study is that not only we use this systemic risk model to assess bank credit risk, but also that we identify the market price of risk and therefore the contribution of risk premia to the CDS spreads. We do this by carrying out a Bayesian estimation of the model by MCMC methods exploiting both the cross section and time series of CDS spreads, so that we can estimate the risk neutral and objective parameters. This econometric methodology can efficiently tackle the high dimensionality of the estimation problem at hand and help quantify estimation uncertainty.

A number of studies investigate the distress risk premia embedded in the term structure of CDS spreads (Pan and Singleton (2008), Longstaff et al. (2011), Zinna (2013)). However, these earlier studies focus on emerging market sovereign entities and simply develop one-factor models that are uninformative about systemic risk. On the other hand, there is an extensively growing literature on systemic credit risk following the 2007-09 crisis, though with significant differences in the models developed. Structural approaches model directly the balance-sheet variables of financial institutions in order to learn about the distribution of joint shocks (see e.g. Lehar (2005)). However, structural models rely on strong assumptions not only on the liability structure of financial institutions, but also on the marginal and joint distribution of risks (Giglio (2012)). For this reason, other studies such as Acharya et al. (2010), and Adrian and Brunnermeier (2009), among others, look at the historical distributions of returns. Another strand of the literature focuses on extracting marginal default probabilities from CDS spreads. This literature generally relies on copula methods, which are often calibrated on the cross section of equity returns, to infer joint default probabilities. For example, Huang, Zhou, and Zhu (2009) use a credit portfolio risk model to compute a risk-neutral measure of aggregate systemic risk.[4] In contrast, a key advantage of our approach is that it provides us with a direct measure of the sensitivity of banks (and sovereign) to systemic shocks. Moreover, our affine credit risk model allows us to disentangle the impact of distress risk premia. This is particularly important as risk management should be based on (actual) measures of default risk that are cleaned from the effect of the risk premia. Another advantage of our methodology is that we can estimate our multivariate credit model in one step so that we minimize the estimation error, which generally increases with the number of estimation steps. Our framework is based on CDS data that provide an accurate assessment of tail event risk.[5][6]

Despite the importance of bank systemic credit risk, and sovereign credit risk, there is relatively little research exploring the sources of commonality. Acharya et al. (2011) provide substantial evidence on the two-way feedbacks between sovereign and bank credit risk. Kallestrup, Lando, and Murgoci (2012) find that bank risk is an important factor in the determination of sovereign credit spreads. Other studies looking at the effects of bailouts on

[4] This method has then been extended in a series of papers (Huang, Zhou, and Zhu (2010a, 2010b), Lahmann and Kaserer (2011)). Other relevant studies on measuring systemic risk are Chan-Lau and Gravelle (2005), Avesani, Pasqual, and Li (2006), Giesecke and Kim (2011), Lo Duca, and Peltonen (2013), De Nicolò and Lucchetta (2010), and Lamont et al. (2013). Of particular interest is also the study of Billio et al. (2012), in that the insurance sector in addition to the financial sector is also modeled to quantify risk concentration and causation. Giglio et al. (2013) propose: i) a criterion to evaluate systemic risk measures based on their ability to predict low quantiles of real macroeconomic aggregates; and ii) an index that aggregates individual measures of systemic risk.

[5] CDSs are essentially 'bet' on the banks' strength and therefore indicate the risk that the institution will fail. In particular, Hart and Zingales (2011) argue that the CDS is a better indicator than equity because equity prices may disguise the probability of default when assets are very volatile.

[6] A number of studies focus on constructing measures of expected shortfall, which would result from multiplying the probability of systemic default by the expected tail loss. We instead focus on a narrow definition of systemic risk, similarly to Ang and Longstaff (2013), among others, based on the probability of joint defaults. We therefore abstract from modelling a time-varying loss given default. This approach is also consistent with the evidence that the probability of joint defaults is the main driver of the variability in the expected shortfall indicator (Lahmann and Kaserer (2011)).

sovereign credit risk include Sgherri and Zoli (2009), Attinasi, Checherita and Nickel (2009), Alter and Schueler (2011), Mody and Sandri (2011), Ejsing and Lemke (2011), and Gray and Jobst (2011). Taken together, these studies suggest that sovereign and bank credit risk are increasingly linked, and therefore support our modeling set up. In turn, our results complement the finding of these studies using a novel asset pricing perspective.

The rest of the paper is organized as follows. Section 2 discusses an intensity-based multivariate default risk model. Section 3 presents the data. Section 4 introduces the model restrictions and econometric methodology. We then present and discuss the empirical results. We focus on systemic credit risk in Section 5 and bank-specific credit risk in Section 6. Section 7 turns to analyzing the distress risk premia. Finally, Section 8 concludes the paper.

2 Pricing CDS and Modeling Default

A credit default swap (CDS) is an insurance contract in which the protection seller takes on the risk of an agreed credit event against the payment of a premium from the protection buyer. The protection seller covers the loss the protection buyer incurs contingent on the credit event (protection leg). In return, the protection buyer pays an annuity to the protection seller (premium leg). The protection buyer stops paying the premium to the seller if the credit event takes place before maturity. Pricing a default swap contract consists of finding the fair swap premium such that the contract has zero value at inception.

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

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

Similarly, given a constant risk-neutral fractional recovery $R^{\mathbb{Q}}$, the present value of the protection leg of a credit default swap is

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

Under the no-arbitrage condition, the fair value of $CDS(t,T)$ is derived such that the protection leg $PR(t,T)$ is equal to the premium leg $P(t,T)$,

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

We model default allowing for two credit events. The first is an idiosyncratic shock that only triggers the default of an individual bank. This is done in a reduced-form fashion, whereby the idiosyncratic default is modeled as the first jump of a Poisson process. In contrast, the second credit event captures a systemic shock, which is also modeled as a Poisson process. However, during a systemic episode every bank can eventually default. But crucially during such event the probability of default is bank specific, i.e. each bank loads differently on the systemic intensity factor. Fundamentally, this loading will ultimately inform us on each bank's relative exposure to systemic risk.

Assume that the economy is populated by N banks and one sovereign. Default of a generic entity i is modeled as the first jump of a Cox process with intensity $\lambda_{i,t}$ (Jarrow and Turnbull (1995), Lando (1998), Duffie and Singleton (1999)). However, there is strong anecdotal and statistical evidence that defaults tend to be correlated. For this reason, we model the intensity $\lambda_{i,t}$ of a generic entity i as the sum of the idiosyncratic intensity ($X_{i,t}$) and the (scaled) common intensity ($\alpha_i Y_t$)

$$\lambda_{i,t} = \alpha_i Y_t + X_{i,t}, \quad i = 0, 1, \ldots, N, \tag{4}$$

where $i = 0$ denotes the sovereign and $i = 1, \ldots, N$ the banks. The common intensity (Y_t) is scaled by the bank-specific coefficient (α_i), which only takes positive values. When a systemic shock arrives, each entity has probability of default α_i. Such events can therefore trigger a cascade of defaults. For this reason, the common intensity Y_t is assumed to reflect the overall state of the economy, inducing correlation across the single entities' default intensities. By contrast, the intensity $X_{i,t}$ captures the idiosyncratic default risk of each entity. The default intensity (4) is a generalization of the specification used by Duffie and Garleanu (2001), where they assume $\alpha_i = 1$. A similar specification to ours has also been used by Mortensen (2006) for corporate CDS spreads, Ang and Longstaff (2013) for sovereign CDS spreads, and Feldhutter and Nielsen (2012) for the pricing of CDOs.

The bank-specific intensity $X_{i,t}$ follows a square-root (Cox, Ingersoll and Ross (1985)) process under the risk-neutral measure

$$dX_{i,t} = (\kappa_{0,i} - \kappa_{1,i}^{\mathbb{Q}} X_{i,t})dt + \sigma_i \sqrt{X_{i,t}} dZ_{i,t}^{\mathbb{Q}}, \tag{5}$$

where $\kappa_{0,i}$, $\kappa_{1,i}^{\mathbb{Q}}$ and σ_i are positive constants, and $Z_{i,t}^{\mathbb{Q}}$ is a standard Brownian motion under the risk-neutral measure $\mathbb{Q}$. This process allows for heteroskedasticity as the variance of the Brownian motion is state dependent. Similarly, the common intensity Y_t follows the process

$$dY_t = (\kappa_{0,Y} - \kappa_{1,Y}^{\mathbb{Q}} Y_t)dt + \sigma_Y \sqrt{Y_t} dW_t^{\mathbb{Q}}, \tag{6}$$

where the standard Brownian motion is now $W_t^{\mathbb{Q}}$, which is independent of $Z_{i,t}^{\mathbb{Q}}$.

Modeling default as in eq. (4) and using the square-root dynamics for the intensities as in eq (5) and (6), it follows that expectations in eq. (1) and (2) can be solved analytically using the transform approach of Duffie, Pan, and Singleton (2000). We can thus easily find the fair value of $CDS(t,T)$ (see Appendix A). Finally, to close the model, we assume an essentially affine market price of risk for the diffusion risk in eq. (5) and (6) as in Duffee (2002), among others. As a result, the systemic and idiosyncratic intensities follow a square-root process also under the objective measure $\mathbb{P}$

$$\begin{aligned} dY_t &= (\kappa_{0,Y} - \kappa_{1,Y}^{\mathbb{P}} Y_t)dt + \sigma_Y \sqrt{Y_t} dW_t, && (7) \\ dX_{i,t} &= (\kappa_{0,i} - \kappa_{1,i}^{\mathbb{P}} X_{i,t})dt + \sigma_i \sqrt{X_{i,t}} dZ_{i,t}, && (8) \end{aligned}$$

where W_t and $Z_{i,t}$ are Brownian motions under the objective measure, which are still mutually independent. Finally, $\pi_Y = \kappa_{1,Y}^{\mathbb{Q}} - \kappa_{1,Y}^{\mathbb{P}}$ and $\pi_i = \kappa_{1,i}^{\mathbb{Q}} - \kappa_{1,i}^{\mathbb{P}}$ determine the systemic and idiosyncratic default risk premia.[7]

[7] An alternative specification of the market price of risk is the extended market price of risk proposed by Cheridito, Filipovic and Kimmel (2007). Under this specification, not only the mean reversion parameters, but also the unconditional mean parameters, are allowed to change under P and Q. However, this parametric form of the market price of risk requires the Feller condition to be satisfied both under P and Q in order to avoid arbitrage opportunities. In practice, this implies that a series of non-linear constraints need to be implemented

3 The Data

The choice of the banks to be included in the study is a delicate issue. In this study, we limit the number of banks to seven for the US and UK in order to alleviate the estimation burden. More fundamentally, we only focus on systemically important banks. The banks included in our analysis are chosen according to their relevance based on market capitalization and provision of banking services in the country at hand. Specifically, we follow the Financial System Stability Assessment (FSSA) in the choice of the banks both for the US and UK.[8] The US banks include: JP Morgan (JPM), Bank of America (BoA), Citi, Wells Fargo & Co (WFC), Goldman Sachs (GS) and Morgan Stanley (MS). In addition to these six banks included in the US FSSA, we extent the analysis also to Capital One Financial (COF). The UK FSSA includes the following seven banks: HSBC, Barclays (BARC), the Royal Bank of Scotland (RBS), Santander UK (SUK), Lloyds Banking Group (LBG), Standard Chartered (STAN) and Nationwide (NW). This group of UK institutions consists of the five major UK-owned banks, the biggest foreign-owned bank subsidiary (i.e. Santander UK) and the largest building society (i.e. Nationwide). These seven institutions account for 71 percent of total assets in banking system, 80 percent of loans and roughly 90 percent of retail deposits in the UK, and for this reason, these banks are defined as the 'seven major UK banks' (IMF, 2011). Though the US banking system is less concentrated than the UK system, the seven banks we consider account for more than 60 percent of the US banking sector. Moreover, in the US there is a substantial difference in the size of the largest banks and the remaining banks. As a result, this group of selected US banks has the benefit of being rather homogeneous and representing a group of systemically important banks (IMF (2010)).[9] A detailed analysis of

in the estimation. We find that imposing these constraints slows down significantly the convergence of the algorithm and deteriorates the pricing of the term structure of CDS. For these reasons, in this study, we use the more parsimonious essentially affine market price of risk.

[8] The Financial Sector Assessment Program (FSAP) is a comprehensive and in-depth assessment of a country's financial sector carried out by the International Monetary Fund and the World Bank. It is a key instrument of the Fund's surveillance and provides input to the Article IV consultation. In jurisdictions with financial sectors deemed by the Fund to be systemically important, financial stability assessments under the FSAP are a mandatory part of Article IV surveillance, and are supposed to take place every five years. Each individual country's FSAP concludes with the preparation of a Financial System Stability Assessment (FSSA), which focuses on issues of relevance to IMF surveillance and is discussed at the IMF Executive Board together with the country's Article IV report.

[9] According to the list of top 50 holding companies produced by the National Information Center, the seventh largest holding company for the US is GE Capital. But GE Capital though large is a non-bank financial company (Veronesi and Zingales (2010)). In order to preserve the homogeneity of our group of banks we therefore include Capital One Financial. Note also that for other banks it is difficult to find a term structure of CDS spreads of adequate quality.

the US and UK banking systems is provided in the Internet Appendix.[10]

The data for this study include the sovereign and bank CDS spreads for the term structure of one-, three-, five-, seven- and ten-year contracts. The notional for the US sovereign and bank CDS contracts is specified in dollars, whereas the notional for the UK sovereign and bank CDS contracts is specified in Euros.[11] The data are obtained from *Markit* and cover weekly (Wednesday) CDS prices over the period from January 2008 to July 2013. The choice of the sample is mainly dictated by the limited liquidity of the US and UK sovereign CDS market prior to January 2008. Fundamentally, this sample includes the main financial events that characterize the recent financial crisis.

Table 1 reports summary statistics of the five-year CDS spreads for the US and UK sovereigns and the indicated banks. The average spreads for the US banks range from a low of 100 basis points for JP Morgan to a high of 238 basis points for Morgan Stanley. The average spreads for the UK banks range from a low of 93 basis points for HSBC to a high of 191 basis points for RBS. Thus, the average spreads for US and UK banks are of similar magnitudes. However, US banks' spreads generally display a larger range of variation. For example, the spreads of Morgan Stanley range from a minimum of 94 basis points to a maximum of 1104 basis points, whereas the spreads of LBG range from a minimum of 31 to a maximum of 372 basis points. Interestingly, the average CDS spread for the US sovereign is about two-thirds of the average spread for the UK sovereign, 38 and 62 basis points, respectively. This stylized fact, combined with the evidence on the average spreads of US and UK banks, suggests that UK sovereign credit risk is more closely related than US credit risk to its domestic banks' credit risk. Turning to the autocorrelation statistic, the US and UK sovereign CDS spreads are highly autocorrelated (0.95 and 0.97, respectively). Autocorrelations of the UK banks' CDS spreads are larger than 0.90, whereas the autocorrelations of the US banks' CDS spreads are smaller than 0.90 except for Bank of America, Citi and Capital One.

The principal component analysis for the changes in the 5-year sovereign and bank CDS

[10] The Internet Appendix can be found on the authors' personal websites.

[11] The choice of the currency of denomination is dictated by the high liquidity of the US dollar contract for the US banks, and the Euro denominated contract for the UK banks (including the UK sovereign). The only exception consists of the US sovereign, for which the contract denominated in Euros is generally more liquid than the contract denominated in US dollars, as the former protects the investor for the US dollar depreciation in the event of default. However, for large part of our sample the two contracts traded at the same price. And, when the two contracts traded at different prices, the difference was small possibly reflecting the small probability of defaulting of the US Treasury. More fundamentally, we opted for the US sovereign CDS contract denominated in US dollars to be consistent with the currency of denomination of the US bank contracts.

spreads (not reported) shows that there is a significant degree of comovement. The correlations between US banks' CDS premia and the first principal component range from 62 percent for Capital One to 96 percent for Morgan Stanley. The US sovereign has a correlation of 27 percent with the first principal component. Similarly, the correlations between UK banks' CDS premia and the first principal component range from 61 percent for Standard Chartered to 92 percent for LBG. The UK sovereign though has a correlation of 50 percent with the first principal component. Taken together, these stylized facts support our modeling choice of a common intensity jointly determining banks' CDS premia. It is also apparent that there is a comovement between sovereign credit risk and domestic banks' credit risk, and this is particularly important for the UK. In addition, Figure 1 shows that the US sovereign CDS premia are significantly lower than US bank CDS premia. Thus, the data seem to support the sovereign ceiling hypothesis. In contrast, in a few occasions the UK sovereign CDS premia edge higher than HSBC's CDS premia. This result is possibly explained by the international nature of HSBC's activities, and therefore is consistent with the empirical evidence on the sovereign ceiling (Durbin and Ng (2005)).[12]

4 Model Estimation

In this section, we propose a Bayesian estimation method, which is particularly suitable for continuous-time financial models (Johannes and Polson (2009)). This method allows us to simultaneously estimate model parameters and latent factors, and quantify the uncertainty around the estimates. For example, post-estimation calculations, such as the distress risk premia, are based on highly non-linear functions of the estimated parameters. As a result, quantifying the uncertainty of such objects in a frequentist context would be highly complicated, whereas it is rather straightforward in a Bayesian context (Bauer (2011)). Also, Bayesian methods are often used in the estimation of term structure models of interest rates as the likelihood function is generally high dimensional and strongly non-linear in the model parameters, being also characterized by multiple local maxima (Ang, Dong, and Piazzesi (2007)). In addition, the dynamic of the underlying factors driving the pricing are generally highly persistent and the estimation sample is relatively small. As a result, maximum likelihood

[12] Also, Santander UK CDS premia in few occasions have traded lower than the UK sovereign. But given the domestic focus of Santander UK this stylized fact is more puzzling.

estimates of term structure models can suffer from small-sample bias (Bauer, Rudebush and Wu (2012)). These concerns are instead limited in a Bayesian context, as for example it does not require assumptions on the order of integration in the factors. More fundamentally, the Bayesian method can provide us with exact finite sample properties of the estimates, despite the fact that the intensities are non-normally distributed, and the CDS price is a non-linear function of the underlying intensities.

The rest of the section is organized as follows. Subsection 4.1 presents the state-space model representation. Subsection 4.2 analyses the model restrictions. Subsection 4.3 describes the Bayesian estimation methodology. And finally Subsection 4.4 briefly discusses parameter estimates and model performance.

4.1 State-Space Representation

A natural way to proceed is to cast the model into a state-space form, which regards the systemic and idiosyncratic default intensity factors as latent states. By discretizing the objective dynamics (7) and (8) with a small time interval τ, we have the following state equations:

$$Y_t = \kappa_{0,Y}\tau + (1 - \kappa_{1,Y}^{\mathbb{P}}\tau)Y_{t-\tau} + \sigma_Y \sqrt{\tau Y_{t-\tau}}\omega_t, \quad (9)$$

$$X_{i,t} = \kappa_{0,i}\tau + (1 - \kappa_{1,i}^{\mathbb{P}}\tau)X_{i,t-\tau} + \sigma_i \sqrt{\tau X_{i,t-\tau}} z_{i,t}. \quad (10)$$

At time $t = 1, ..., T$, prices for the 1-, 3-, 5-, 7- and 10-year maturities are recorded and they are stacked in the vector CDS_t^{obs}. Prices are assumed to be collected with measurement error, so the measurement equation is

$$CDS_{i,t}^{obs} = CDS(Y_t, X_{i,t}, \Theta) + \epsilon_{i,t}, \quad \epsilon_{i,t} \sim N(0, \Sigma_i) \quad (11)$$

where $CDS(\cdot)$ is the pricing function as in equation (3), which depends on the systemic (Y_t) and idiosyncratic ($X_{i,t}$) factors and model parameters (Θ). To reduce the computational burden of estimation, we use a common coefficient driving the volatilities of the CDS pricing error at different maturities, so that $\Sigma_i = \sigma_i I$, where I is a diagonal matrix. The complete measurement equation stacks together the measurement equations of the seven banks and the sovereign $CDS_t^{obs} = \left[CDS_{0,t}^{obs}; CDS_{1,t}^{obs}; ...; CDS_{6,t}^{obs}; CDS_{7,t}^{obs}\right]$. As a result, 40 CDS prices are collected at each date t.

Similarly to Pan and Singleton (2008), among others, the interest rate is assumed to be constant. Following Ang and Longstaff (2013), among others, we assume a constant loss given default of 50 percent, implying $R^{\mathbb{Q}} = 0.50$.

4.2 Model Specification and Restrictions

We impose the following two restrictions to the model. First, we normalize the sensitivity parameter of the sovereign α_0 to one. This implies that α_i measures bank i systemic sensitivity relative to the one of the sovereign. From an econometric perspective, this restriction is simply a convenient way of rescaling the systemic exposures. Second, we assume that the sovereign can only default in conjunction with a systemic event. Taken together, the two restrictions imply that sovereign CDS premia are priced only by the systemic intensity, effectively using a one-factor model. But it is important to stress that: i) the systemic intensity also enters the pricing of bank CDS premia; and ii) the model is estimated jointly using both the sovereign and bank CDS premia. The systemic intensity should therefore reflect mainly bank systemic risk and not sovereign risk. In other words, we do not expect to price sovereign CDS premia accurately, as other factors independent of bank systemic risk could in principle affect sovereign credit risk (Kallestrup (2012)). It therefore remains an empirical question to ascertain whether the inclusion of the sovereign CDS premia helps identify this systemic component, and to what extent can we price sovereign CDS premia within this model setup.

Our restrictions are similar in spirit to the ones used by Ang and Longstaff (2013). More fundamentally, our second restriction is mainly dictated by economic theory. In particular, it is consistent with the sovereign ceiling literature, which predicts that corporate yields pay a firm risk premium over the government bond yield. Intuitively, the corporate's cost of capital compensates the investor not only for the country risk but also for the idiosyncratic risk of the firm. But the government and the corporate operate in the same macro environment and are therefore exposed to the same macro-economic risks. Such risks in our model are captured by the systemic intensity of default. In this regard, our model also relates to the modeling framework of Dittmar and Yuan (2008). However, our second restriction is also motivated by the two-way feedbacks between financials and sovereigns suggested by Acharya et al. (2011).

4.3 Bayesian Inference

Bayesian estimation approximates the posterior distribution of parameters and states given the whole set of observations, $p(\Theta, H|Y)$, where Θ denotes the parameters, H denotes the latent states (i.e. the systemic and the N bank-specific default intensities), and $Y = \{CDS_t^{obs}\}_{t=1}^T$ denotes the data. Direct sampling from the posterior distribution $p(\Theta, H|Y)$ is often not feasible due to its high dimensionality or complicated form. The Markov Chain Monte Carlo (MCMC) method solves the problem of simulating from this complicated target distribution by simulating from simpler conditional distributions. Precisely, by applying the Bayes' rule, the posterior density can be decomposed as follows:

$$p(\Theta, H|Y) \propto p(Y|H, \Theta)p(H|\Theta)p(\Theta), \tag{12}$$

where $p(Y|H, \Theta)$ is the likelihood function given the states and the parameters, $p(H|\Theta)$ is the probability distribution of states conditional on the parameters, and $p(\Theta)$ is the prior density of the parameters. We can then iteratively draw from the full conditionals $p(\Theta|H, Y)$ and $p(H|\Theta, Y)$. The parameter set Θ and the state set H can be further broken into smaller blocks.

We first draw the parameters conditional on the data and the states. The objective mean-reversion parameters $\kappa_{1,Y}^{\mathbb{P}}$ and $\kappa_{1,i}^{\mathbb{P}}$ and variances of measurement errors σ_i^2 have conjugate priors, with normal and inverse Gamma posterior, respectively. Thus, we can sample directly from their posterior distributions using the Gibbs sampler. However, it is not possible to sample directly from the full conditional posterior distributions of the rest of the parameters. For these parameters, we use the slice sampling method recently developed by Neal (2003). We then draw the latent states individually, conditional on the parameters and the data. Also in this case the posterior distributions are non-standard so that we again use the slice sampling method. In sum, we implement a hybrid MCMC algorithm that combines the Gibbs sampler with a series of slice sampling steps. By repeatedly simulating from the conditional distribution of each block in turn, we get samples of draws. These draws, beyond a burn-in period, are treated as variates from the target posterior distribution.[13][14] The algorithm is

[13] More specifically, we perform 100,000 replications, of which the first 50,000 are burned-in. We then save 1 every 10 draws of the last 50,000 replications of the chain so that the draws are independent. The priors used in this study are diffuse, and their distributions are chosen for convenience using a number of earlier papers (e.g., Johannes and Polson (2009)).

[14] To estimate the continuous time model from discrete data, we use its Euler discretized version. In a term

described in detail in the Internet Appendix.

4.4 Parameter Estimates and Model Performance

We estimate the model separately for the US and UK, whereby for each country we include the major seven banks and the sovereign. Table 9 reports the posterior means and 95 percent credible intervals of parameter estimates resulting from the Bayesian estimation. The parameters are generally estimated with very tight credible intervals. The only exception regards $\kappa_1^{\mathbb{P}}$, but this parameter is notably difficult to estimate when using only CDS data. For the US sovereign and banks, almost all risk-neutral mean-reversion parameters ($\kappa_1^{\mathbb{Q}}$) are negative except that of Morgan Stanley and Capital One, implying the default intensities are explosive in most cases under the risk-neutral measure. However, $\kappa_1^{\mathbb{P}}$s are all positive, indicating that the default intensities are still stationary under the objective measure $\mathbb{P}$. Of interest is that the US systemic default intensity mean-reverts faster than the bank-specific intensities. As for the UK, the risk-neutral mean-reversion parameters of the banks are also negative, whereas the sovereign parameter is positive. The UK intensities are stationary under $\mathbb{P}$ as $\kappa_1^{\mathbb{P}}$s are positive, and the UK systemic intensity mean-reverts faster than the bank-specific. Recall that the difference between $\kappa_1^{\mathbb{P}}$ and $\kappa_1^{\mathbb{Q}}$ drives the default risk premia. Therefore, there could be a significant risk premium embedded into the pricing of the US and UK bank CDS contracts. The risk premia will be carefully analyzed in Section 7.

The analysis of the standard deviations of the measurement errors suggests that the model prices well most of the maturities. For the US, Wells Fargo and JP Morgan have the smallest standard deviations, 7.0 and 7.7 respectively, while Morgan Stanley's standard deviation is the largest (38.0). For the UK, HSBC has the lowest standard deviation of 6.1, while the sovereign has the highest of 22.3. Model fit is further analyzed in Table 2, which reports the mean absolute percentage pricing errors (MAPPE) for the CDS spreads of the indicated maturities. Overall, the model precisely prices the five-, seven- and ten-year

structure model, Stanton (1997) finds that approximation errors in the conditional moments of the process of certain diffusions is negligible for time interval up to a month. However, the discretized states could take negative values. In classical methods, this complication is usually dealt with by setting the likelihood to a large negative values and truncating states at small values (Feldhutter and Lando (2008)). In Bayesian methods, however, this complication can be more easily addressed by imposing parameter and state constraints on priors and by discarding sample draws from posterior distributions that violate such constraints (Gelfand, Smith, and Lee (1992)). In this way, the empirical distribution can closely track the continuous time distribution implied by the square-root process. Moreover, we develop a single-move algorithm that draws the states one at a time, where each state can be regarded as a parameter with a non-negative prior.

contracts. For a number of banks, the pricing errors of the three-year contract are also of comparable magnitude. In contrast, the pricing of the one-year contracts is relatively poor. This is also a standard result in the literature that is usually explained by the low liquidity of the one-year contract (Pan and Singleton (2008)).

The MAPPEs for the sovereigns over the 2008-13 period are around 50 to 60 percent for maturities greater than five-year. Such large pricing errors for the sovereigns are not surprising though, given that the sovereign CDS premia are only priced by the systemic intensity, which mainly reflects bank systemic risk. Therefore, there may be other factors that also determine sovereign risk. However, as we look at the MAPPE over the 2009-13 sub-period, the pricing errors for the sovereigns significantly drop. This drop is particularly important for the UK sovereign, where the MAPPEs is roughly half for the three- to ten-year maturities. This result supports the view that over the 2009-13 the sovereign and the banks become more intimately linked. By contrast, during the earlier stages of the crisis, market participants do not fully price the 'future' bank bailouts and the consequent increase in sovereign credit risk.

5 Systemic Credit Risk

In this section, we present the US and UK systemic credit risk intensities estimated using the term structure models. We relate their evolution to the main financial, macroeconomic and political events that occurred in the 2008-13 period. We then explore econometrically the determinants of systemic bank credit risk. Next, we report the systemic sensitivities, and quantify the impact of systemic bank credit risk on total bank credit risk. Finally, we discuss whether the inclusion of the sovereign CDS premia in the model affects the estimation of systemic bank credit risk.

5.1 Systemic Bank Credit Risk 2008-13

There are several reasons why it is important to study the properties of the intensity estimated from a term structure model, instead of looking directly at CDS premia. First, the intensity implied by the model well summarizes the information contained in the entire term structure. Second, it reflects the current probability of default in contrast to a long-term average, implied in longer-term CDS premia. In contrast, the one-year CDS is generally illiquid and therefore is not sufficiently responsive to changes in credit risk. Third, the intensity of default is not affected by default risk premia, and therefore is a more direct measure of default risk. Taken together, these observations suggest that the intensity of default has the potential to be more responsive, and therefore more informative on the evolution of systemic credit risk than CDS spreads at a specific maturity.

Figure 2 plots the time series estimates of the systemic intensities of default, and the 95 percent credible intervals, for the US and UK. It is apparent that the two intensities display a similar evolution over the sample, though there are also significant differences. The US intensity has been generally lower than the UK intensity. Despite both the US and UK intensities reach their peaks around March 2009, the response of the UK intensity to Lehman's default is more immediate and substantial than that of the US intensity. More generally, the US intensity shows more pronounced turning points, whereas the UK intensity displays a remarkable and persistent reaction to the European debt crisis. The average UK intensity (60 basis points) is roughly twice the average of the US intensity. Similarly, the median of the UK intensity is 40 basis points, being roughly twice the median of the US intensity. In contrast, the volatility of the UK intensity is 65 basis points versus 40 for the US intensity. Taken together, these results suggest that the US and UK intensities are driven by few extremely high values, and the graphical evidence suggests that these values refer to the period after Lehman Brothers' default, and to some extent also to the worsening of the European crisis. In what follows, we try to relate the main turning points of our measures of systemic risk to the major political and financial events of the 2008-2013 period.

US systemic credit risk shows a few turning points over the start of the sample. These episodes coincide with the introduction of the Term Securities Lending Facility (TSLF) by the Federal Reserve (Mar-2008), the rescue plan for Fannie Mae and Freddie Mac (Jul-2008), and Lehman Brothers' default (Sep-2008). Then, in an attempt to rescue the US financial sector, the House of Representatives passes the US$700 billion Troubled Asset Relief Program (TARP) (Oct-2008). And, soon after, the Federal Reserve announces the creation of the Term Asset-Backed Securities Loan Facility (TALF) (Nov-2008). But the consequent drop in systemic risk proves to be short lived. Thereafter, systemic credit risk skyrocketedly reaches its peak around the time the G20 announces a trebling of the IMF's resource to US$750 billion. As of January 2010, US systemic credit risk is back to the pre-2009 levels, after a stark fall. Systemic credit risk worsens again in conjunction with the Greek rescue packages (March-2010), as the focus of concern switches from the private sector to the public sector.

Then, the European Financial Stability Facility (EFSF) is established, and the results of the banks' stress tests are published. In the following months, US systemic credit risk drops and reaches its sample lows. It rebounds though around the time Standard & Poor's announces that America's debt would no longer be classed as top-notch triple A. More fundamentally, this episode comes at the time when policymakers are confronted with a slowing global economy and a systemic crisis in Europe.

Similarly to the US intensity, the UK intensity reaches a peak around Mar-2008. But during that period the UK intensity takes much higher values than the US intensity. In particular, the peak is dated shortly after the nationalization of Northern Rock in Feb-2008. But the UK intensity drops remarkably after Mar-2008. During this period, the Bank of England launches the Special Liquidity Scheme (SLS), which allows for banks to swap their high-quality mortgage-backed and other securities for UK Treasury Bills. But with Lehman Brothers' default, the UK systemic risk reaches unprecedented levels. In order to respond to the heightened risks, the Bank of England extends the drawdown period for the SLS and concludes a reciprocal swap agreement with the Federal Reserve. At the same time, the Financial Security Authority prohibits short-selling of financial shares.

However, despite these measures, the UK systemic credit risk only falls in Oct-2008. This is about the same time when the US authorities passes the TARP, and a series of additional measures are taken by the UK authorities. In fact, the UK support package is announced on the 8th of October.[15] On the same day, there are co-ordinated interest rate cuts of 50 basis points (including the Bank of England, the FED and the ECB). Over the following months, a number of additional measures are announced by the UK authorities. However, these measures do not prevent UK systemic risk to take off, as shown by our measure of UK systemic risk. The fall in systemic risk is only temporary, and UK systemic risk reaches its peak around the same time the US intensity also reaches its peak. But the rise of the UK intensity starts earlier than the rise of the US intensity, reaches much higher values and is more persistent. In fact, around the time of Lehman's default, the US and UK intensities are about the same levels, but soon after the UK intensity is much higher than the US intensity. Then in September 2009, the US and UK intensities are back to similar levels.

In the autumn of 2009, UK systemic credit risk begins to rise again. This rise reaches a

[15] This package includes provision of capital to UK incorporated banks, guarantee for new short to medium-term senior unsecured debt issuance and the extension and widening of the SLS.

peak around the time the rescue packages for Greece are announced. The following peak is at the time the EFSF is established. Then, UK systemic credit risk decreases until August 2010. But since then, in conjunction with the worsening of the Eurozone crisis, the UK intensity markedly increases. Towards the end of 2010, the US intensity is decreasing, while the UK intensity is still increasing. During the second quarter of 2011, both systemic intensities approach unprecedented low levels. However, the UK intensity dramatically increases as the European crisis becomes more systemic, affecting the much bigger Italian and Spanish economies (Oct-2011). Precisely, the UK intensity reaches its relative peak as of November 2011, when debt yields across the Eurozone rise dramatically. There is anecdotal evidence that around this time investors become increasingly pessimist about Europe's prospect for resolving its crisis. UK systemic credit risk stops rising around the time Euro area leaders agree on a new fiscal compact, and the Long Term Refinancing Operation (LTRO) is announced by the ECB. The turning point though is in July 2012 when at the Global Investment Conference in London Mario Draghi reassured the markets by saying that "... Within our mandate, the ECB is ready to do whatever it takes to preserve the Euro. And believe me, it will be enough"(Jul-2012). As a result, the UK systemic bank intensity first reaches and then remains at extremely low levels until the end of the sample.

5.2 What Drives Systemic Risk?

So far we have shown that major turning points of our measures of systemic bank credit risk are associated with relevant financial, macroeconomic and political events that took place over the 2008-13 period. We also find that the events that are deemed to be important to explain the evolution of systemic credit risk are generally the same for the US and UK. However, the extent to which the US and UK systemic intensities respond to these events differs. For this reason, in this section we shed new light on the determinants of systemic credit risk by relating its evolution to a set of global and domestic variables. This approach of regressing the estimated intensity on a set of explanatory variables is common in the academic literature (Longstaff, Mithal, and Neis (2005), Pan and Singleton (2008), Longstaff et al. (2011), and Ang and Longstaff (2013)).

However, no consensus has emerged yet in the literature on whether credit spreads should be specified in levels or first differences in the regression analysis. Although a level specification can offer advantages in assessing the economic impact of the individual covariates, there are clear disadvantages when assessing model fit (Doshi et al. (2011)). As the intensity of default largely inherits the statistical properties of the credit spreads, to some extent it is subject to the same debate. In our study, we follow Collin-Dufresne, Goldstein, and Martin (2001) and Ang and Longstaff (2013), among others, and specify our model in (weekly) differences. We use this specification as it allows us to rely on standard measures of model fit, and therefore assess the contribution of the independent variables in terms of R-square.[16]

The choice of the independent variables is also a delicate issue, as potentially many variables co-move with systemic credit risk. We therefore try to follow earlier studies in the choice of the variables. The global variables we use are the same for the US and UK. Precisely, we use: the weekly changes in the Asian CDX index; the weekly changes in the Emerging Market CDX, and; the weekly changes in the German CDS. The data for these variables are obtained from *Markit*. As for the domestic variables we use: the returns on the S&P500 for the US, and the returns on the FTSE for the UK; the weekly changes in the respective spot five-year government yields for the US and UK; the weekly changes in the volatility index, VIX for the US and VFTSE for the UK; the weekly changes in the CDX IG index for the US, and ITraxx main index for the UK. The data for these variables are from Bloomberg. We also construct the illiquidity measure of Hu, Pan, and Wang (2013) for the US and UK.[17]

Table 3 presents the regression results. We find that the US bank systemic risk is strongly positively related to changes in investment grade corporate spreads. We also find that systemic risk increases as the 5-year yield and the stock market fall. Interestingly, positive changes in the Asian CDX and German CDS spreads are associated with rising systemic risk in the US. In contrast, the Emerging Market CDX enters with a negative sign. This may result from multicollinearity with the Asian CDX in particular. But it may also suggest that some emerging market economies at times have decoupled from advanced economies (Kose, Otrok, and Prasad (2012)). The R-square of the regression is 42 percent, thus we can explain almost

[16]By expressing our model in first differences we can also alleviate the problem of multicollinearity in the dependent variables. The correlation usually drops when moving from levels to changes. This is particularly important as the correlation across asset classes generally increases during crises.

[17]Hu, Pan and Wu (2013) propose a market-wide liquidity measure by exploiting the connection between the amount of arbitrage capital in the market and observed price deviations in US Treasury bonds. Their measure of liquidity can capture episodes of liquidity crises of different origins and magnitudes across the financial market. Moreover, there is evidence that this measure provides information above and beyond existing liquidity proxies. For all these reasons, we decided to use their measure of liquidity, and we have replicated this measure for the UK.

half of the variation in systemic risk using both domestic and global variables. We then compute the R-squares resulting from regressing US systemic risk on global and domestic variables separately. Interestingly, the R-square on the regression on domestic variables alone (36 percent) is almost as large as the R-square including both domestic and global variables. In contrast, the R-square drops to 28 percent when only global variables are included. This result suggests that domestic variables are more important than global variables for the US.[18]

Next, we further investigate the stability of our estimates, which may be affected by correlated regressors. We do this by first dropping the corporate variable, then the German CDS and finally both variables. We find that when the corporate variable is excluded the R-square drops by 8 percent, and only by 1 percent when the German CDS is dropped from the regression. Interestingly, when both variables are excluded the R-square drops by 11 percent. More fundamentally, the sign and significance of the coefficients of the remaining variables, with the only exception of the illiquidity measure, is robust to the exclusion of the German CDS and corporate spreads.[19]

We repeat the same analysis for the UK systemic intensity, and obtain similar results to those for the US. However, the R-square for the UK is substantially higher (56 percent). We also find that investment corporate spreads are even more important for the UK. Further, we find that when we drop the German CDS from the regression, the R-square does not change. In contrast, the R-square drops by 27 percent when we exclude the ITraxx. One explanation could be that the ITraxx, as mainly includes European corporates, is picking up some of the European crisis risk.[20] The stock market is statistically significant only when both the German CDS and the ITraxx are excluded from the regression. In sum, we find that investment grade corporate spreads strongly co-move with our measures of systemic bank credit risk, and domestic variables, such as the corporate spreads, the 5-year yield and the domestic stock market, explain a substantial share in the variation of our measures of systemic

[18] If domestic and global variables were not correlated with each other, then the sum of the R-squares from the separate regressions should equal the R-square of the regression with both global and domestic variables. So there is a fair amount of information that is picked up by the domestic variables when the global variables are excluded. But global variables are still important as they are significant in the regression including both domestic and global variables.

[19] The illiquidity measure shows a puzzling negative and significant coefficient at the 10% significant level, indicating that increasing systemic risk is associated with increasing liquidity. However, this result seems to be driven by the high correlation between corporate spreads and the illiquidity measure. In fact, when the corporate spreads are excluded the illiquidity measure is no longer statistically significant.

[20] UK banks are not included in the ITraxx, whereas the ITraxx mainly includes European corporates. For this reason, we have also repeated the regression using the yield on UK corporate bonds. The results are qualitatively and quantitatively consistent.

risk.

5.3 Systemic Bank Exposures

We now present the estimates of the systemic exposures. The focus therefore shifts from the time-series dynamics, analyzed in the previous section, to the *cross-sectional* dimension of systemic risk. More specifically, we assess each bank exposure to a systemic event, and separate the contribution of systemic credit risk from the overall bank credit risk.

Table 4 presents the estimates of the bank specific coefficients (α_i) of eq. (4). Recall that this parameter denotes bank i's probability of default in the event of a systemic event. Also, the sovereign coefficient is fixed at 1, so that banks' coefficients are re-scaled with respect to the sovereign probability of default in the event of a systemic shock. Precisely, the estimated value of α_i for the bank denotes the ratio of the conditional probability of default for the bank to that of the sovereign. For example, the value of α_i of JP Morgan is 2.02, which implies that in conjunction with a systemic event, the probability that JP Morgan defaults is roughly two times higher than the one of the US sovereign.

Interestingly, we find that all the US banks have a systemic exposure greater than one. The average value of the systemic exposures for the US banks is 3.76, whereas the median value is 3.34. Citi has the highest exposure of 6.80, whereas JP Morgan has the lowest exposure of 2.02. This result may reflect the fact that during our sample JP Morgan generally traded at lower CDS premia than the other US banks. In contrast, Citi's exposure is higher than Morgan Stanley despite the fact that Citi's CDS premia are on average lower than Morgan Stanley. Similarly, Bank of America has lower CDS premia but higher systemic exposure than Goldman Sachs.

The average value of the systemic exposures for UK banks is 1.36. This result for the UK is therefore in stark contrast to the result for the US. In fact, the average systemic exposure of UK banks is roughly three times lower than the average systemic exposure of US banks. As a result, the UK sovereign has roughly three times higher probability of default than the US sovereign during a systemic crisis. This result may reflect the much larger size of the UK banking sector relative to the size of the UK economy.

HSBC has systemic exposure statistically not different from one. This result can possibly be reconciled with the fact that at times HSBC CDS premia traded lower than the UK sovereign CDS premia, reflecting the international focus of HSBC's activities. Similarly, Santander UK that is a foreign-owned bank has systemic exposure not different from one. LBG and Nationwide display systemic exposures of roughly 1.3, whereas RBS, Standard Chartered and Barclays have the highest exposures of 1.67, 1.63 and 1.58, respectively. It is therefore possible to identify three distinct groups of banks in terms of their exposure to systemic risk. In general, it is less evident for the UK than for the US that banks' systemic exposures reflect the average CDS premia over the period. That said, we provide in Table 5 an alternative measure of systemic risk that is not affected by the overall riskiness of the bank. We define this measure as the systemic intensity weight (SIW), which is computed as $\alpha_i Y_t / (\alpha_i Y_t + X_{i,t})$, so that the systemic risk is standardized by the total default risk of the bank ($\lambda_{i,t}$), and is therefore comparable across banks of different riskiness.

A number of interesting results follow. First, on average Wells Fargo has the highest SIW (63 percent), despite its relatively low systemic risk exposure (3.03). Thus, although Wells Fargo has a relatively low probability of defaulting during a systemic event, the nature of its default risk is largely systemic. Citi also displays a high average SIW, but differently from Wells Fargo, it has high average CDS premia. In contrast, idiosyncratic risk largely explains Goldman Sachs, Morgan Stanley and Capital One default risk. For JP Morgan and Bank of America systemic risk is on average about as important as idiosyncratic risk. More fundamentally, we find that the balance between systemic credit risk and idiosyncratic credit risk strongly varies over time. In fact, SIWs can range from zero to hundred percent, with the only exceptions of Wells Fargo with a minimum of 7 percent, and Capital One with a maximum of 91 percent. Therefore the nature of banks' credit risk at times is idiosyncratic, at times systemic, and at times a mix of the two.[21] However, given this strong variability, it is also informative to look at the median. It is apparent that there exist one group of high systemic risk, that consists of Wells Fargo, JP Morgan and Citigroup, and a separate group of low systemic risk banks, including Bank of America, Goldman Sachs and Morgan Stanley. Capital One displays an even lower median SIW of 19 percent, highlighting its idiosyncrasy.

Similarly to the US result, UK bank estimates of SIWs show substantial time variation.

[21] A natural question is whether assuming a common loss given default across banks, instead of estimating a bank specific loss given default, can affect our results. Different values of the loss given default may affect the estimates of the probabilities of default, and therefore the estimates of the systemic exposures. But the SIW, ie the split between idiosyncratic and systemic risk, is robust to different values of the loss given default, as the loss given default is common to idiosyncratic or systemic defaults (specifically $R^{\mathbb{Q}}$ - roughly - multiplies $\alpha_i Y_t + X_{i,t}$ in the pricing of the CDS). Also, this assumption will not affect the time series properties of systemic risk. We can therefore conclude that this assumption, though not trivial, does not affect the bulk of our analysis.

Moreover, the analysis of the median SIWs shows that systemic credit risk explains a large fraction of HSBC, Standard Chartered and Barclays' credit risk. On the contrary, the type of credit risk of RBS, LBG, Santander UK and Nationwide is largely idiosyncratic. Thus, banks with a larger domestic source of revenues display lower SIWs, so that this separation largely reflects the geographic footprint of the UK banks. Systemic credit risk therefore explains a larger fraction of total credit risk of more internationally oriented banks. It is also true though that HSBC, Standard Chartered and Barclays not only are internationally focused, but also display on average lower CDS spreads. This in turn suggests that the superior riskiness of the remaining banks is captured by the idiosyncratic intensities that are the focus of Section 6.

5.4 Sovereign and Systemic Bank Credit Risk

Our baseline specification includes the term structure of sovereign CDS premia together with the term structure of bank CDS premia. This modeling specification allows us to scale banks' exposures with respect to the sovereign. A natural question is whether the inclusion of the sovereign not only plays the role of a scaling factor - individual bank exposures to a systemic credit event are expressed relative to the sovereign exposure - but can also at times substantially affect the evolution of the probability of a credit event taking place. We try to answer to this question by repeating the estimation of our model without including sovereign CDS premia. Then, we compare the new estimate of the systemic credit risk intensity (excluding the sovereign) with the earlier estimate (including the sovereign).

However, in order to make the level of the two estimates of systemic credit risk comparable, we impose that the systemic exposures of Wells Fargo and HSBC are fixed at 3.02 and 1.00, respectively. These values correspond to the estimates of Wells Fargo and HSBC systemic exposures in Table 4.[22]

Figure 3 presents the estimates of the systemic intensities for the US and UK without including the sovereign (green line), and the old estimates including the sovereign (blue line). We find that the inclusion of the sovereign does not affect substantially the estimates of systemic risk both for the US and UK. Therefore, the systemic risk intensity does reflect bank credit risk and the inclusion of the sovereign only plays the role of scaling banks' systemic exposures.

[22] We chose WFC and HSBC as these are the banks for which systemic risk on average explains a larger fraction of their credit risk. However, in principle we could have chosen any other couple of banks.

So far we have shown that the inclusion of sovereign CDS spreads does not materially affect our estimate of systemic risk, so that systemic risk is a measure of systemic bank risk. Further, in the baseline model specification, sovereign CDS premia are priced only by this factor, whereas bank CDS premia are priced by two factors. For all these reasons, it is therefore natural to expect larger pricing errors for the sovereign CDS spreads than for bank CDS spreads. However, in order to improve the pricing accuracy of the sovereign premia, an alternative model specification would consist of pricing sovereign CDS premia not only as a function of the systemic factor, but also of a sovereign-specific factor, i.e., $\lambda_{0,t} = Y_t + X_{0,t}$. We implement this additional model specification to check the robustness of the estimated systemic intensity.

We find that the new specification now prices accurately the sovereign CDS premia, with pricing errors comparable to the banks' pricing errors. The MAPPEs for the 5- and 7-year maturities are 10 and 6 percent, respectively, for the US sovereign, and 11 and 7 percent for the UK sovereign, as shown in the Internet Appendix.[23] Moreover, consistently with the results of section 4.4, the MAPPEs become substantially smaller over the 2009-2013 subsample. More fundamentally, Figure 3 shows that the evolution of the systemic intensity, resulting from the model specification that allows for a sovereign-specific intensity (red line), is essentially the same as the systemic intensity resulting from the simple baseline specification (blue line), though the red line takes lower values than the blue line in order to compensate for the presence of the sovereign-specific intensity. Of course, as a result, the estimated bank systemic exposures will also become larger to compensate for the lower values of the systemic intensity, as bank i systemic risk is denoted by $\alpha_i Y_t$. But, notably, the ordering of the banks in terms of the systemic exposures (α's) and the estimates of the SIWs do not change. In sum, the systemic bank intensity is well identified irrespective of the model specification used. Further, although the inclusion of a sovereign-specific intensity improves the pricing of sovereign CDS spreads, the findings resulting from our simpler baseline specification are qualitatively and quantitatively robust. And because the focus of the paper is on bank risk, and not on sovereign risk, in what follows we refer to our baseline specification.

[23] Note also that this alternative specification relies on the same Euler discretization method used in Section 4.1. We can therefore conclude that the Euler discretization used is not responsible for the large sovereign pricing errors displayed in Table 2.

6 Bank-specific Credit Risk

We now turn to analyzing the properties of the bank-specific or idiosyncratic component of credit risk. We first perform a principal component (PC) analysis to better understand the covariance structure of bank-specific intensities of default across banks. Thus, this analysis provides an alternative perspective, to the systemic exposure analysis, on the cross-sectional structure of bank *idiosyncratic* default risk.

The first US PC is a level factor, explaining mostly the evolution of Morgan Stanley and Goldman Sachs' intensities of default.[24] The first PC also correlates significantly (around 50 percent) with Citi, JP Morgan and Wells Fargo's default risk, whereas Bank of America and Capital One default intensities display the lowest correlation (25 percent). The second PC largely reflects the evolution of Capital One's default risk, and it correlates positively with the group of high SIWs that consists of Citi, JP Morgan and Wells Fargo. However, taken together, the first three PCs do not explain more than 60 percent of the variation in the intensities of Citi, JP Morgan, Wells Fargo and Bank of America. This suggests that the systemic intensity well captures the comovement in US bank spreads.

Figure 4 presents the estimated bank-specific intensities for the US, which are grouped according to the PC analysis. A number of interesting results emerge: i) Morgan Stanley's intensity takes the highest values by far; ii) Bank of America's intensity reaches a peak during the European crisis, differently from the other banks; iii) the behavior of Capital One's spreads is largely idiosyncratic during the 2008-09 crisis; iv) Wells Fargo and JP Morgan's default intensities take the lowest values; and v) the pick-up in US banks' default risk during the European crisis seems to be largely bank specific.

We then repeat the PC analysis for UK bank-specific intensities of default. The first PC correlates positively with all bank-specific intensities, though it largely represents HSBC and Barclays, and to a lower extent Santander UK, LBG and RBS. The second PC even more highlights the specific behavior of HSBC, as it correlates negatively with HSBC and positively with all the other banks. The third PC instead captures the idiosyncratic behavior of Nationwide. In addition, the specificity of Standard Chartered is emphasized by the fact that the first three PCs only explain 20 percent of its evolution. The first three PCs also do not explain a substantial fraction of the variability of the intensities of RBS, LBG and

[24] In order to economize the space, we do not report the table with the principal component analysis (PCA). Note that the PCA is performed on the first difference of bank-specific intensities of default.

Santander UK. We can therefore conclude also for the UK that the systemic intensity removes large part of the comovement in the UK bank spreads.

Visual inspection of Figure 5 reveals that the introduction of the UK support package is beneficial to all the UK banks. However, its impact strongly varies across banks, and for this reason it is largely captured by the idiosyncratic intensities of default rather than by the systemic. RBS and Nationwide display the largest drop in the default intensity of around 200 basis points, and LBG, Barclays and Santander UK of 100 basis points. Also the intensities of HSBC and Standard Chartered drop, though to a lower extent, in conjunction with the bank bailouts. However, differently from the other banks, Standard Chartered reaches a peak in 2009. After this episode the intensities of Standard Chartered and HSBC closely track each other. Similarly, the intensities of RBS, LBG and Santander almost overlap for large part of the sample, indicating that differences in the level of CDSs simply stem from differences in the systemic exposures. In sum, the inspection of the bank-specific intensities highlights important differences in default risk across banks that are not easily captured by simply looking at the CDS spreads.

6.1 European Crisis

In this sub-section, we examine the extent to which the systemic and the bank-specific intensities of default co-move with European stock market returns. By doing this, we shed light on bank exposures to the European crisis through asset prices, which may provide an alternative perspective to banks' direct exposures (e.g., bank A's holdings of European securities). Asset prices should indeed reflect not only direct but also indirect bank exposures to European risk. Moreover, a key advantage of our model is that we can focus on bank *idiosyncratic* exposures to the European crisis.

We regress the systemic and bank-specific default intensities on selected European stock market returns. In particular, we focus on Greece, Ireland, Portugal, Spain and Italy. However, the correlation among these stock markets during the crisis is particularly high, and as a result our regression would suffer from multicollinearity. For this reason, we first regress individual countries' stock market returns on the weekly returns on the DAX index. We then regress the individual bank intensities on the residuals obtained from the first stage regressions. From an economic perspective, we use the German stock market in the first stage as this should capture to large extent Eurozone's systemic risk. As a result, the residuals from the first step regressions can be interpreted as the idiosyncratic risk of the country at hand. From a statistical viewpoint, by doing this we aim to reduce the correlation among the dependent variables. We indeed find that the resulting residuals display much lower correlations than the original countries' equity returns.

Table 5 reports the results of the regressions of the systemic and bank-specific intensities on the countries' orthogonalized equity returns, i.e., the residuals resulting from the first stage regressions. We also include the returns on the DAX as a separate dependent variable. The total R-square refers to the regression including the returns on the DAX in addition to the distressed countries' orthogonalized equity returns.[25] For the US, positive returns on the German and Italian stock markets are associated with negative changes in the systemic intensities (fall in credit risk), being significant at the 1 percent and 10 percent level, respectively. For the UK, the German, Italian and Greek equity returns are significant at the 1 percent. We find R-squares of 28 and 41 percent respectively both for the US and UK regressions. When we drop the DAX variable, the R-square falls to 3 percent for the US, and 10 percent for the UK.

As we move on to the bank-specific intensity regressions, the DAX explains a smaller share of variation than in the regressions of the systemic intensities. These results suggest that the DAX (Germany) is indeed a good model-free proxy for systemic European risk.[26] Moreover, we find that the Italian stock market returns are significant for Bank of America and Goldman Sachs. Also the Greek and Irish returns are significant for Bank of America, though Irish returns enter with a positive sign.[27] For the UK, we find a widespread significant negative effect of the Italian and Greek equity returns. Spanish returns are also important to explain the evolution of LBG and Santander's credit risk. Irish returns enter with a positive sign also in the case of UK banks.

European returns can largely explain JP Morgan, Bank of America and Citigroup's credit risk. That said, European risk explains even a larger share of the variability of UK banks' credit risk, with the only exception of Nationwide. More fundamentally, the R-squares in the

[25] Note that by construction countries' equity returns - proxied by the residuals of the first stage regressions - are independent of the returns on the DAX. As a result, the estimates of the estimated coefficients for the countries' equity returns do not change with the inclusion of the returns on the DAX.

[26] Alternatively, taking for given that the German CDS is a measure of systemic risk, the results confirms that our estimate is a measure of systemic risk.

[27] This result may suggest that for Bank of America what matters are the returns of the Italian and Greek stock markets relative to the Irish's stock market return. But, of course, we cannot rule out the presence of some residual multicollinearity.

regressions excluding Germany are generally higher for the UK than for the US banks. We can therefore conclude that US banks' credit risk is largely exposed to Eurozone's *systemic* risk, proxied by the German CDS, whereas UK banks' credit risk is also substantially affected by individual European countries' returns. In particular, as far as UK banks are concerned, it is apparent that in the recent crisis the Italian and Greek stock markets play a central role. In general, there is no clear link between the geographic footprints of the banks and their sensitivities to the performances of the European stock markets. This may in turn suggest that indirect exposures are important to assess the impact of the European crisis on the credit risk of US and UK banks.

7 Distress Risk Premia

Investors in corporate bonds are exposed to different sources of risk and, for this reason, demand distinct risk premia for each of these risks. The financial literature generally focuses on two risk premia: the jump-at-event risk premium and the distress risk premium. The jump-at-event risk premium compensates the investor for the surprise jump in price that may occur in conjunction with a credit event that triggers the CDS contract. This risk premium is generally measured by the distance between the risk-neutral and the objective arrival rate of the credit event (Driessen (2005)). However, by modeling the term structure of CDS premia we can only extract the risk-neutral intensity of default, whereas we would need additional data on the actual probability of default to estimate the objective intensity of default.[28] Thus, similarly to previous studies (Pan and Singleton (2008), Longstaff et al. (2011), among others), we focus on the *distress risk premium*. This risk premium compensates the investor for unexpected changes in the arrival rate of the credit event (i.e. the intensity of default $\lambda_{i,t}$). In effect, investors bear the risk that future arrival rates of the credit events differ from the current (objective) consensus expectations implied in the CDS market and, for this reason, demand a distress risk premium.

A simple measure of the distress risk premium is obtained as the difference between the

[28] The jump-at-event risk premium has received considerable attention in the corporate bond literature (Driessen (2005), Berndt et al. (2008), among others). This risk premium is generally measured as the ratio of the risk-neutral and objective intensity of default. Historical (or objective) probabilities of default can be measured using information on company-specific equity prices and balance sheet variables. Ratings and expected default frequency can also be used, as these measures are cleaned from risk premia. For example, Remolona, Scatigna, and Wu (2008) compute historical sovereign probabilities of defaults using ratings.

CDS priced under the risk-neutral probability measure and the CDS priced under the objective measure. The risk-neutral price (CDS), which includes a risk premium, is computed as in eq. (3) using the risk-neutral probability distribution implied by eq. (5) and (6). The pseudo-objective price ($CDS^{\mathbb{P}}$) is also computed as in eq. (3) but using the objective probability ($\mathbb{P}$) implied by eq. (7) and (8). This change of expectation consists of setting the market price of risk to zero (i.e. using $\kappa_1^{\mathbb{P}}$ instead of $\kappa_1^{\mathbb{Q}}$) when pricing the CDS. For this reason, the difference between $\kappa_1^{\mathbb{P}}$ and $\kappa_1^{\mathbb{Q}}$ is indicative of the (unconditional) size of the risk premia.

However, our credit event is driven by two separate intensity processes, which dictate two distinct distress risk premia. More specifically, there is a systemic distress risk premium, which is associated with the probability of a systemic event taking place, and that is common (up to a scaling factor) across banks. In contrast, the idiosyncratic risk premium, which is associated with the idiosyncratic intensity of eq. (8), is bank specific. Thus, we need to quantify the magnitude of each risk premium in turn. We do this by setting to zero the relevant market price of risk. We compute the pseudo-objective systemic price ($CDS^{Y,\mathbb{P}}$) using eq. (5) and (7) by setting to zero the systemic market price of risk, i.e. we replace $\kappa_{1,Y}^{\mathbb{Q}}$ with $\kappa_{1,Y}^{\mathbb{P}}$ when pricing the CDS in eq. (3). Similarly, we compute the pseudo-objective idiosyncratic price ($CDS^{X,\mathbb{P}}$) by setting to zero the idiosyncratic market price of risk, i.e. by replacing $\kappa_{1,i}^{\mathbb{Q}}$ with $\kappa_{1,i}^{\mathbb{P}}$. The total pseudo-objective ($CDS^{\mathbb{P}}$) price is computed by setting to zero both the idiosyncratic and systemic market-prices of risk. We then compute the impact of the distress risk premia on the market prices as $CDS - CDS^{\mathbb{P}}$, where $CDS^{\mathbb{P}}$ varies with the type of risk premium considered (i.e. $CDS^{X,\mathbb{P}}$ for the idiosyncratic, $CDS^{Y,\mathbb{P}}$ for the systemic and simply $CDS^{\mathbb{P}}$ for the total). In order to compare risk premia across banks and maturities, it is standard in the literature (e.g. Pan and Singleton (2008)) to construct the percentage contribution of the relevant risk premium to the spread, e.g. $CRP(M) = \left(CDS(M) - CDS(M)^{\mathbb{P}}\right)/CDS(M)$ for the total risk premium for maturity M. When the actual fitted spread (CDS) exceeds the pseudo-objective ($CDS^{\mathbb{P}}$) spread, the buyer of protection is willing to pay a premium for holding the CDS contract. A detailed description of the risk premia algebra is provided in the Internet Appendix.

7.1 How Large Are the Risk Premia?

Table 6 presents summary statistics for the percentage contribution of systemic ($SCRP$), bank-specific ($ICRP$) and total distress risk premia (CRP) to the five-year spreads. We find that the US banks' total distress risk premia are comparable to the UK banks' risk premia both in terms of level and variability. Such risk premia can be as high as 85 and 87 percent for Wells Fargo and JP Morgan for the US, and 83 and 81 percent for HSBC and Barclays for the UK.

We move on analyzing the SCRP and ICRP. We find that, both for the US and UK, SCRP and ICRP display remarkable variations over time. Their respective variation exceeds the variation of the CRP, indicating that the total distress risk premium is more stable than each of its components. Taken together these results suggest not only that systemic and idiosyncratic risk premia strongly vary over time, but also that they tend to offset each other. We also find that SCRPs are generally larger than ICRPs for the US, whereas there is mixed evidence for the UK.

Moreover, the percentage contribution of the risk premia to the spread, measured by CRP, increases with respect to the maturity of the contract as shown in the Internet Appendix. Of particular interest is that this increase is due to the ICRPs, i.e., the term structure of the total and idiosyncratic term premia is upward sloping, whereas the term structure of systemic risk premia is generally downward sloping for the US banks, and only slightly increasing for the UK banks.

Top panels of Figure 6 show the time-varying decomposition of a theoretical three-year CDS spread resulting from a one-factor model driven by the systemic intensity of default and by the parameters $\kappa^{\mathbb{P}}$ and $\kappa^{\mathbb{Q}}$. In this way, we can assess the contribution of the systemic risk premium versus systemic default risk. It is apparent that the risk premium component is much larger than the risk component. This is true for the UK and even more for the US. Investors therefore are willing to pay a relative high premium to insure from systemic credit events. Although systemic credit events may be low probability events, they can be so severe that the associated distress risk premia are particularly high.

To complete the analysis we decompose the bank CDS spreads into the following four components: i) idiosyncratic credit risk; ii) idiosyncratic distress risk premia; iii) systemic credit risk; and iv) systemic distress risk premia. We leave the computational details to the Internet Appendix. Figure 6 shows the decomposition of the three-year CDS premia into the four components for selected banks. The fraction of the systemic risk premia to systemic default risk is generally higher than the fraction of idiosyncratic risk premia to idiosyncratic default risk. This result seems to hold for both the US and UK banks. There is one caveat though: banks with low levels of credit risk, reflected in low levels of idiosyncratic risk, also display particularly large idiosyncratic risk premia. This is the case for example of JP Morgan, Wells Fargo and HSBC. For the remaining banks, the results seem to suggest that the distress risk premia associated with a unit of systemic risk are much higher than the risk premia associated with a unit of idiosyncratic risk.

Figure 6 also helps evaluate the evolution of risks and risk premia during the sample. The US charts show that Goldman Sachs and Morgan Stanley (not reported) hit first as the 2008 increase in their CDS premia is largely idiosyncratic. In contrast, the pick-up in CDS premia in 2009 is mainly systemic due to rising systemic risk premia. Also for the UK, systemic risk rises in conjunction with the 2008-09 crisis, whereas the subsequent rise in credit risk is mainly driven by idiosyncratic risk for RBS and LBG, and by the systemic component for HSBC. In sum, the systemic risk component of CDS spreads is mainly explained by large systemic risk premia, and it generally decreases with respect to the maturity of the contract for the US, suggesting that shorter term CDS contracts can be particularly informative on systemic risk. In contrast, idiosyncratic risk premia display an upward-sloping term structure, and generally explain a lower fraction of idiosyncratic credit risk.

7.2 What Drives the Risk Premia?

We now investigate the determinants of distress risk premia for each bank in turn. We do this by regressing weekly changes in the bank percentage contribution of distress risk premia to the five-year spreads.[29] The choice of the independent variables is again a delicate issue. For this reason, we try to be consistent with the set of variables we have used to explore the determinants of systemic credit risk. However, we use a more restrictive set of variables, as we drop all the variables that refer to the CDS market, as they may contain a similar type of risk premium. Thus, the four remaining variables we focus on are the weekly returns on the S&P 500 (FTSE) for the US (UK), the weekly changes in the VIX (VFTSE) for the US (UK), the weekly changes in the five-year spot government yield for the respective country, and the weekly changes in the Hu, Pan, and Wang (2013) measure of illiquidity for the US (UK). In sum, our set of variables captures changes in general sentiment, economic and liquidity

[29] The time series of the risk premia for the US and UK are displayed in the Internet Appendix. As previously noted, the total risk premia display a rather stable evolution for a number of banks. In addition, the analysis of the confidence intervals shows that the risk premia are precisely estimated, despite the well-known difficulty in accurately estimating the objective dynamics.

conditions of the market.

Table 7 shows that US banks' distress risk premia strongly relate to the return on the stock market. In particular, positive changes in the risk premia are associated with negative returns on the stock market. Moreover, US banks' risk premia fall as the five year government yield rises. This may suggest that a rising yield signals higher expected short-term yields, reflecting improving macroeconomic conditions, and is therefore associated with lower distress risk premia. The R-squares range from 16 to 31 percent. In particular, Bank of America and Capital One have the highest R-squares, which is consistent with the fact that distress risk premia account for a large fraction of their spreads.

Similarly for the UK we find that the returns on the stock market and changes in the five-year government yields are important determinants of banks' distress risk premia. However, the stock market returns are significant only for Santander UK and Barclays. The R-squares range from a minimum of 2 percent for Nationwide to a maximum of 17 percent for HSBC. In sum, decreasing five-year yields and a rising stock market point towards lower bank distress risk premia, with this latter effect being particularly strong for US banks.

8 Concluding Remarks

This paper studies systemic bank credit risk over the 2008-13 period for the US and the UK. We develop a multivariate credit risk model, which captures joint defaults of banks. The probability of such a systemic event occurring varies over time and exposures to systemic risk vary across banks. However, banks can also default due to an idiosyncratic event. For this reason, this model allows us to disentangle how much of a banks' default risk is systemic versus bank-specific. Moreover, investors demand distinct default risk premia as they are exposed to unexpected changes in the systemic and idiosyncratic intensities of default.

We find that US and UK systemic bank credit risks display a similar evolution, though also present important differences. For example, UK systemic risk strongly reacts to the start and worsening of the Eurozone crisis. However, they both react to the same major political and financial events. Further, the evolution of systemic bank credit risk is strongly related to changes in corporate spreads and European risk. We also find that systemic credit risk on average represents about half of total bank credit risk, but its importance strongly varies over time. Of interest is also that the systemic component of CDS spreads is explained by high risk premia, which in turn are mainly driven by the equity market and government yields. Thus, investors demand a high compensation for being exposed to a rare but severe event such as a cascade of bank defaults. This finding has important policy implications as it suggests that even a small reduction in systemic risk can have substantial effects on banks' funding costs through a reduction in the risk premia.

Our findings also bear important insights on the relationship between sovereign and bank systemic credit risk. We find that UK banks' systemic exposures are about the same as the UK sovereign exposure, whereas US banks have on average roughly three times larger systemic exposure than the US sovereign. We argue that this result can reflect the large size of the UK banking sector relative to the size of the UK economy. Taken together, the results suggest that sovereign and bank systemic risk are particularly interlinked in the UK.

Appendix A: Pricing Credit Default Swaps

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

$$D(T) = E^{\mathbb{Q}}\left[\exp\left(-\int_0^T r_t dt\right)\right]. \tag{1}$$

Given the specification for the default intensity (4), the dynamics (5) and (6), and assuming that r_t and $\lambda_{i,t}$ are independent, it follows that the price of the CDS spread for bank i is:

$$CDS_i(t,T) = \frac{(1-R^{\mathbb{Q}})E^{\mathbb{Q}}\Big[\int_t^T D(s)(\alpha_i Y_s + X_{i,s})\exp\Big(-\int_t^s \alpha_i Y_u + X_{i,u}du\Big)ds\Big]}{E^{\mathbb{Q}}\Big[\int_t^T D(s)\exp\Big(-\int_t^s \alpha_i Y_u + X_{i,u}du\Big)ds\Big]}. \tag{2}$$

As the dynamics (5) and (6) are modeled using square-root processes, the transform approach proposed by Duffie, Pan and Singleton (2000) can be used to analytically solve the expectations in (2). Therefore, we end up with

$$CDS_i(t,T) = \frac{(1-R^{\mathbb{Q}})\int_t^T D(s)(A(s,Y_t)G(s,X_{i,t}) + \alpha_i B(s,X_{i,t})H(s,Y_t))ds}{\int_t^T D(s)A(s,Y_t)B(s,X_{i,t})ds}, \tag{3}$$

where

$$
\begin{aligned}
A(s, Y_t) &= A_1(s) \exp(A_2(s) Y_t), & (4)\\
B(s, X_{i,t}) &= B_1(s) \exp(B_2(s) X_{i,t}), & (5)
\end{aligned}
$$

$$
\begin{aligned}
G(s, X_{i,t}) &= (G_1(s) + G_2(s) X_{i,t}) \exp(B_2(s) X_{i,t}), & (6)\\
H(s, Y_t) &= (H_1(s) + H_2(s) Y_t) \exp(A_2(s) Y_t), & (7)
\end{aligned}
$$

and

$$
\begin{aligned}
A_1(s) &= \exp\left(\frac{\kappa_{0,Y}(\kappa_{1,Y}^{\mathbb{Q}} + \psi)s}{\sigma_Y^2}\right)\left(\frac{1-v}{1-ve^{\psi s}}\right)^{2\kappa_{0,Y}/\sigma_Y^2}, & (8)\\
A_2(s) &= \frac{\kappa_{1,Y}^{\mathbb{Q}} - \psi}{\sigma_Y^2} + \frac{2\psi}{\sigma_Y^2(1-ve^{\psi s})}, & (9)\\
B_1(s) &= \exp\left(\frac{\kappa_{0,i}(\kappa_{1,i}^{\mathbb{Q}} + \phi)s}{\sigma_i^2}\right)\left(\frac{1-\theta}{1-\theta e^{\phi s}}\right)^{2\kappa_{0,i}/\sigma_i^2}, & (10)\\
B_2(s) &= \frac{\kappa_{1,i}^{\mathbb{Q}} - \phi}{\sigma_i^2} + \frac{2\phi}{\sigma_i^2(1-\theta e^{\phi s})}, & (11)\\
G_1(s) &= \frac{\kappa_{0,i}}{\phi}(e^{\phi s} - 1)\exp\left(\frac{\kappa_{0,i}(\kappa_{1,i}^{\mathbb{Q}} + \phi)s}{\sigma_i^2}\right)\left(\frac{1-\theta}{1-\theta e^{\phi s}}\right)^{2\kappa_{0,i}/\sigma_i^2+1}, & (12)\\
G_2(s) &= \exp\left(\frac{\kappa_{0,i}(\kappa_{1,i}^{\mathbb{Q}} + \phi)s}{\sigma_i^2} + \phi s\right)\left(\frac{1-\theta}{1-\theta e^{\phi s}}\right)^{2\kappa_{0,i}/\sigma_i^2+2}, & (13)\\
H_1(s) &= \frac{\kappa_{0,Y}}{\psi}(e^{\psi s} - 1)\exp\left(\frac{\kappa_{0,Y}(\kappa_{1,Y}^{\mathbb{Q}} + \psi)s}{\sigma_Y^2}\right)\left(\frac{1-v}{1-ve^{\psi s}}\right)^{2\kappa_{0,Y}/\sigma_Y^2+1}, & (14)\\
H_2(s) &= \exp\left(\frac{\kappa_{0,Y}(\kappa_{1,Y}^{\mathbb{Q}} + \psi)s}{\sigma_Y^2} + \psi s\right)\left(\frac{1-v}{1-ve^{\psi s}}\right)^{2\kappa_{0,Y}/\sigma_Y^2+2}, & (15)\\
\psi &= \sqrt{\kappa_{1,Y}^2 + 2\alpha_i\sigma_Y^2}, \quad \phi = \sqrt{\kappa_{1,i}^2 + 2\sigma_i^2}, & (16)\\
v &= (\kappa_{1,Y} + \psi)/(\kappa_{1,Y} - \psi), \quad \theta = (\kappa_{1,i} + \phi)/(\kappa_{1,i} - \phi). & (17)
\end{aligned}
$$

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Table 1: Summary Statistics

	Mean	StdDev.	Min.	Med.	Max.	Serial Corr.	nobs.
US Sovereign	38	16	6	39	95	0.96	289
JP Morgan	100	31	44	94	208	0.90	289
Bank of America	175	83	49	151	482	0.95	289
Citigroup	199	98	71	171	638	0.93	289
Wells Fargo	106	37	59	96	306	0.90	289
Goldman Sachs	180	81	66	149	579	0.89	289
Morgan Stanley	238	131	94	190	1104	0.88	289
Capital One Financial	175	105	77	124	519	0.97	289
UK Sovereign	62	29	5	63	164	0.97	289
Royal Bank of Scotland	191	75	58	178	400	0.94	289
Lloyds Banking Group	177	77	31	167	372	0.96	289
HSBC	93	30	41	82	173	0.93	289
Santander UK	154	77	45	143	350	0.98	289
Barclays	142	48	46	133	266	0.91	289
Standard Chartered	118	51	43	102	330	0.95	289
Nationwide	151	38	82	144	287	0.92	289

The table reports summary statistics for the 5-year CDS spreads for the US and UK sovereigns and the indicated banks. The sample consists of weekly observations from January 2, 2008 to July 9, 2013.

Table 2: Parameter Estimates

Panel A: United States					
	k_0	$k_1^{\mathbb{P}}$	σ	$k_1^{\mathbb{Q}}$	σ_ϵ
US Sov	0.172	2.121	0.307	-0.029	19.856
	[0.164;0.180]	[0.549;3.684]	[0.297;0.317]	[-0.059;0.004]	[19.447;20.273]
JPM	0.007	0.991	0.160	-0.481	7.730
	[0.005;0.009]	[0.239;1.750]	[0.157;0.163]	[-0.493;-0.470]	[7.550;7.910]
BoA	0.171	0.521	0.167	-0.087	20.479
	[0.158;0.183]	[0.131;0.904]	[0.159;0.175]	[-0.099;-0.075]	[20.069;20.900]
Citi	0.069	0.921	0.209	-0.371	17.496
	[0.059;0.078]	[0.234;1.595]	[0.203;0.215]	[-0.395;-0.347]	[16.996;18.003]
WFC	0.007	1.360	0.151	-0.597	7.018
	[0.006;0.009]	[0.353;2.361]	[0.147;0.155]	[-0.620;-0.574]	[6.820;7.212]
GS	0.173	0.560	0.210	-0.095	22.527
	[0.158;0.187]	[0.142;0.966]	[0.203;0.218]	[-0.108;-0.083]	[22.055;22.991]
MS	0.559	0.771	0.333	0.031	38.233
	[0.526;0.592]	[0.199;1.346]	[0.321;0.346]	[0.014;0.049]	[37.460;38.985]
COF	0.577	0.911	0.226	0.272	15.749
	[0.553;0.602]	[0.363;1.438]	[0.214;0.238]	[0.262;0.282]	[15.435;16.063]

Panel B: United Kingdom					
	k_0	$k_1^{\mathbb{P}}$	σ	$k_1^{\mathbb{Q}}$	σ_ϵ
UK Sov	0.352	1.580	0.304	0.057	22.296
	[0.344;0.362]	[0.453;2.716]	[0.285;0.323]	[0.029;0.082]	[21.840;22.751]
RBS	0.017	0.459	0.168	-0.292	14.922
	[0.011;0.023]	[0.105;0.823]	[0.165;0.171]	[-0.300;-0.283]	[14.618;15.232]
LBG	0.005	0.432	0.158	-0.261	14.353
	[0.002;0.009]	[0.103;0.774]	[0.155;0.161]	[-0.269;-0.253]	[14.050;14.646]
HSBC	0.001	0.973	0.147	-0.491	6.060
	[0.000;0.001]	[0.230;1.722]	[0.145;0.149]	[-0.501;-0.481]	[5.920;6.197]
SUK	0.016	0.488	0.168	-0.272	10.904
	[0.012;0.019]	[0.112;0.868]	[0.165;0.171]	[-0.279;-0.264]	[10.673;11.130]
BARC	0.004	0.739	0.160	-0.436	8.018
	[0.002;0.006]	[0.169;1.304]	[0.158;0.162]	[-0.445;-0.427]	[7.836;8.201]
STAN	0.000	0.771	0.136	-0.411	10.600
	[0.000;0.001]	[0.173;1.362]	[0.133;0.139]	[-0.430;-0.394]	[10.304;10.889]
NW	0.022	0.607	0.173	-0.277	10.854
	[0.016;0.028]	[0.155;1.078]	[0.168;0.177]	[-0.287;-0.267]	[10.616;11.086]

The table reports posterior means and 95 percent credible intervals (in square bracket). The k_0 parameters are reported in percentage and the σ_ϵ in basis points. The estimation is performed with the Bayesian algorithm described in section 4, based on weekly data from January 2, 2008 to July 9, 2013. The measurement error standard deviations are reported in basis points.

Table 3: Pricing Errors

Panel A: United States										
	2008-13					2009-13				
	1yr	3yr	5yr	7yr	10yr	1yr	3yr	5yr	7yr	10yr
US Sov	76.6	71.0	62.6	56.8	53.5	48.1	32.3	39.2	39.3	40.2
JPM	24.1	9.1	4.6	3.9	4.8	29.6	9.7	4.8	3.4	4.1
BoA	38.1	8.8	8.2	9.8	12.0	48.2	7.4	7.1	7.2	7.3
Citi	28.5	9.4	5.2	5.9	7.4	35.6	10.1	4.6	4.0	4.6
WFC	19.3	8.8	4.2	3.0	4.4	23.6	10.6	4.1	2.9	3.7
GS	31.2	6.4	6.2	8.9	11.5	37.9	6.5	5.7	7.5	9.2
MS	23.4	7.2	9.4	12.7	15.8	27.0	7.6	8.3	10.5	12.7
COF	16.2	6.4	6.1	7.2	8.8	21.0	8.2	7.2	6.9	7.1

Panel B: United Kingdom										
	2008-13					2009-13				
	1yr	3yr	5yr	7yr	10yr	1yr	3yr	5yr	7yr	10yr
UK Sov	112.2	70.3	53.6	52.6	49.7	77.2	33.0	24.2	26.4	27.7
RBS	25.2	6.0	3.7	4.2	5.1	30.8	5.4	2.9	3.5	3.5
LBG	31.7	7.4	4.5	5.3	6.2	40.7	7.5	3.4	3.9	4.3
HSBC	22.3	7.3	5.0	2.8	3.7	28.0	7.1	4.8	2.5	2.4
SUK	20.0	5.2	4.5	3.6	4.4	24.1	4.2	3.6	3.3	2.9
Barc	13.0	5.6	3.4	2.9	3.6	15.3	5.8	3.2	2.6	2.3
STAN	29.3	8.4	4.6	3.8	5.0	37.4	9.4	4.5	1.9	2.7
NW	20.0	4.3	4.3	3.0	4.1	19.6	3.4	3.7	2.0	2.8

The table reports the mean absolute percentage pricing errors (MAPPE) for the CDS spreads of the indicated maturities. Left panel reports results for the entire sample (from January 2, 2008 to July 9, 2013), whereas right panel for the sub-sample (from October 14, 2009 to July 9, 2013).

Table 4: Drivers Bank Systemic Credit Risk

Panel A: US Systemic											
		Global					Domestic				
Con	Asia	EM	Germ.	R^2_G	Mkt	Yield	VIX	Corp	Illiq	R^2_L	R^2_{TOT}
-0.26	0.13^a	-0.09^b	0.35^a	22	-1.02^c	-0.10^c	-0.33	0.48^a	-3.58^c	36	42
(0.55)	(0.04)	(0.04)	(0.13)		(0.56)	(0.05)	(0.40)	(0.14)	(1.87)		
-0.29	0.18^a	-0.08^c	0.41^a	22	-1.73^a	-0.15^b	-0.27		-2.69	25	34
(0.61)	(0.04)	(0.04)	(0.15)		(0.63)	(0.06)	(0.41)		(2.09)		
-0.22	0.16^a	-0.10^b		16	-1.27^b	-0.10^c	-0.41	0.49^a	-3.68^c	36	41
(0.55)	(0.05)	(0.04)			(0.57)	(0.05)	(0.42)	(0.13)	(1.89)		
-0.24	0.21^a	-0.08^c		16	-2.04^a	-0.15^b	-0.36		-2.78	25	33
(0.60)	(0.05)	(0.05)			(0.63)	(0.07)	(0.43)		(2.11)		

Panel B: UK Systemic											
		Global					Domestic				
Con	Asia	EM	Germ.	R^2_G	Mkt	Yield	VIX	Corp	Illiq	R^2_L	R^2_{TOT}
-0.5	0.14^b	-0.07^b	0.37^b	35	0.21	-0.12^c	0.03	1.09^a	-1.91	54	56
(0.59)	(0.06)	(0.03)	(0.19)		(0.60)	(0.06)	(0.36)	(0.12)	(1.34)		
-0.44	0.21^a	-0.02	0.93^a	35	-0.96	-0.18^b	0.25		-0.74	25	39
(0.70)	(0.07)	(0.06)	(0.26)		(0.61)	(0.07)	(0.40)		(1.90)		
-0.48	0.16^b	-0.07^b		27	0.12	-0.12^c	-0.01	1.16^a	-2.06	54	56
(0.61)	(0.07)	(0.03)			(0.60)	(0.06)	(0.36)	(0.11)	(1.39)		
-0.37	0.28^a	-0.01		27	-1.44^b	-0.20^b	0.19		-0.95	25	33
(0.74)	(0.08)	(0.07)			(0.64)	(0.09)	(0.40)		(2.18)		

The table reports the regression of weekly changes in systemic intensities (ΔY_t) in basis points on global and domestic variables. Global variables are i) the weekly changes in the Asian CDX index (Asia); ii) the weekly changes in the Emerging Market CDX (EM); the weekly changes in the German 5-yr CDS (Germany). Domestic variables are i) the returns on the S&P500 for the US, and the returns on the FTSE for the UK (Mkt); ii) the weekly changes in the spot 5-yr yield (Yield) for the US and UK; the weekly changes in the volatility index for the US and UK (VIX); the weekly changes in the CDX IG index for the US, and in the ITraxx main index for the UK (Corp); the weekly changes in the measure of illiquidity of Hu, Pan and Wang (2013) (Illiq). R^2_G and R^2_L are the R-squares of the regressions, of which the estimated coefficients are not reported, where only global and local variables are included, respectively. The sample consists of weekly observations from January 2, 2008 to July 9, 2013. Newey-West (1987) standard errors are reported in parenthesis. a, b, and c, denote the 1-, 5-, and 10-percent confidence levels, respectively.

Table 5: Systemic Exposures

	Systemic Exposure		Systemic Intensity Weight				
	α	ci	Mean	StdDev.	Min.	Med.	Max.
JPM	2.02	[1.96;2.08]	51.4	35.8	1.8	65.0	99.7
BoA	3.65	[3.52;3.78]	45.6	38.6	0.8	38.6	98.2
Citi	6.80	[6.57;7.02]	59.4	32.9	2.9	76.1	99.4
WFC	3.04	[2.93;3.13]	63.1	35.7	7.5	83.3	99.8
GS	3.34	[3.20;3.47]	37.4	33.1	0.6	31.7	99.5
MS	4.74	[4.50;4.98]	37.2	32.9	0.5	28.5	98.0
COF	2.70	[2.55;2.85]	34.1	28.1	1.3	19.4	90.8
UK Sov	1						
RBS	1.67	[1.63;1.71]	43.7	30.9	0.6	42.2	99.6
LBG	1.30	[1.27;1.33]	39.5	31.5	0.5	33.7	99.4
HSBC	1.00	[0.99;1.02]	62.8	32.4	1.3	75.1	99.8
SUK	1.02	[1.00;1.05]	40.6	32.6	0.3	37.9	99.3
Barc	1.58	[1.55;1.61]	59.5	32.5	1.2	70.0	98.7
STAN	1.63	[1.60;1.66]	70.6	34.0	1.4	85.6	98.9
NW	1.29	[1.26;1.32]	39.1	26.8	0.5	38.3	98.6

The table presents two measures of systemic risk. Left panel (*Systemic Exposure*) reports the posterior mean of the systemic exposure (α) and its 95 percent credible interval. The value of α is fixed at 1 for the US and UK sovereigns. Right panel (*Systemic Intensity Weight*) reports summary statistics of the time series of the percentage contribution of the systemic intensity to the total intensity (SIW), which is computed as $\alpha_i Y_t / (\alpha_i Y_t + X_{i,t})$ for a generic bank i.

Table 6: Bank Credit Risk and the European Crisis

Panel A: United States								
	Italy	Spain	Portugal	Ireland	Greece	R^2	Germany	R^2_{TOT}
US Syst.	-1.00^c	0.67	-0.47	-0.09	-0.11	3.16	-1.58^a	28.28
JPM	-0.22	-0.08	-0.29^c	0.02	-0.11	5.34	-0.56^a	20.13
BoA	-2.39^b	0.67	0.16	1.26^b	-0.71^c	4.12	-2.83^a	21.79
Citi	-1.69	1.26	-1.34	0.81	0	3.81	-2.19^a	19.32
WFC	-0.26	0.14	-0.26^c	0.08	-0.01	2.99	-0.38^a	14.65
GS	-4.28^c	2.68	-2.46	0.68	-0.92	5.24	-3.04^b	10.75
MS	-16.7	21.38	-13.75	2.53	0.51	8.68	-5.84^c	10.49
COF	1.33	2.67	-3.04	0.18	-0.39	-0.02	-6.59^a	14.87
Panel B: United Kingdom								
	Italy	Spain	Portugal	Ireland	Greece	R^2	Germany	R^2_{TOT}
UK Syst.	-1.71^a	-0.39	0.41	-0.06	-0.68^a	9.79	-2.45^a	41.37
RBS	-3.20^b	2.65	-2.2	1.24^c	-0.27	15.46	-1.08^a	18.78
LBG	-1.50^a	-1.00^c	0.97	0.66^c	-0.70^a	11.52	-1.45^a	23.87
HSBC	-0.31^b	-0.21	0.1	0.06	-0.15^a	8.5	-0.39^a	22.50
SUK	-0.51	-0.83^b	0.1	0.40^c	-0.53^a	9.87	-0.92^a	18.61
BARC	-0.78^c	-0.61	0.58	0.13	-0.35^b	6.68	-0.79^b	15.00
STAN	-0.73^a	0.04	0.02	0.17	-0.18^b	10.37	-0.38^a	17.26
NW	-0.61	-0.54	0.55	0.34	-0.2	1.46	0.12	1.23

The table reports the regressions of weekly changes in default intensities ($\Delta X_{i,t}$) in basis points on contemporaneous weekly returns (in %) on selected European stock indices. Germany denotes the weekly return on the German stock index, whereas Italy denotes the time series of residuals obtained by regressing returns of the Italian stock market on returns on the German stock market. Thus, Italy denotes the component of the Italian stock market returns orthogonal to the German stock market returns. The remaining variables (Spain, Portugal, Ireland and Greece) are obtained in a similar fashion. R^2 refers to the regression excluding Germany, whereas R^2_{TOT} includes also Germany. The sample consists of weekly observations from January 2, 2008 to July 9, 2013. t-statistics are computed using Newey-West (1987) standard errors. a, b, and c, denote the 1-, 5-, and 10-percent confidence levels, respectively.

Table 7: Risk Premia Statistics

Panel A: United States															
	Systemic Risk Premia					Bank-specific Risk Premia					Total Risk Premia				
	Mean	StDev.	Min.	Med.	Max.	Mean	StDev.	Min.	Med.	Max.	Mean	StDev.	Min.	Med.	Max.
JPM	46	17	20	43	81	41	18	3	44	69	87	2	81	87	91
BoA	40	15	16	39	68	31	14	11	30	54	72	2	69	71	79
Citi	46	10	22	47	65	32	13	10	31	61	78	3	72	78	84
WFC	54	11	36	51	80	31	12	3	33	51	85	2	79	85	89
GS	37	15	14	36	75	35	13	6	36	56	72	2	70	72	81
MS	33	12	10	35	67	33	11	10	30	58	67	3	64	67	77
COF	35	10	10	36	52	29	9	18	25	51	64	3	61	63	74
Panel B: United Kingdom															
	Systemic Risk Premia					Bank-specific Risk Premia					Total Risk Premia				
	Mean	StDev.	Min.	Med.	Max.	Mean	StDev.	Min.	Med.	Max.	Mean	StDev.	Min.	Med.	Max.
RBS	37	18	15	31	76	40	18	2	45	62	77	2	71	77	79
LBG	35	19	15	28	77	41	19	1	49	62	77	1	72	77	80
HSBC	49	16	21	50	79	33	18	1	33	66	83	3	74	83	88
SUK	36	22	11	30	77	41	22	3	48	67	78	1	74	78	81
Barc	46	16	21	44	73	35	18	3	36	63	81	3	72	81	85
STAN	56	13	24	58	73	22	16	1	23	59	78	3	71	79	84
NW	36	12	18	34	75	43	12	4	45	62	79	1	76	79	81

This table reports summary statistics for the percentage contribution of default risk premia (CRPs) to the 5-year CDS spreads described in section 7.1. Left panel (*Systemic Risk Premia*) denotes the default risk premia attached to the scaled systemic intensity ($\alpha_i Y_t$). Centre panel (*Bank-specific Risk Premia*) denotes the default risk premia attached to the bank-specific intensity ($X_{i,t}$). Right panel (*Total Risk Premia*) denotes default risk premia attached to the sum of the systemic and bank-specific intensities ($\lambda_{i,t} = \alpha_i Y_t + X_{i,t}$).

Table 8: Drivers of Risk Premia

Panel A: United States						
	Const	Mkt	Yield	VIX	Illiq.	R^2
JPM	0.01	-5.61^a	-1.09^a	-0.01	-0.05	21.57
	(0.03)	(1.99)	(0.32)	(0.01)	(0.07)	
BoA	0	-4.93^a	-0.57^a	0	-0.06	30.81
	(0.02)	(1.55)	(0.21)	(0.01)	(0.06)	
Citi	-0.01	-6.02^c	-1.46^b	0.02	-0.29	24.03
	(0.05)	(3.15)	(0.58)	(0.03)	(0.20)	
WFC	0	-12.67^a	-1.08^b	-0.05^c	-0.17	16.35
	(0.05)	(3.18)	(0.54)	(0.03)	(0.17)	
GS	0	-4.43^a	-0.45^a	0	-0.04	28.11
	(0.02)	(1.30)	(0.17)	(0.01)	(0.06)	
MS	-0.01	-5.85^a	-0.62^b	0	-0.1	25.2
	(0.03)	(1.97)	(0.29)	(0.01)	(0.11)	
COF	-0.01	-6.96^a	-0.53^b	0	-0.12^c	31.1
	(0.02)	(1.84)	(0.22)	(0.01)	(0.07)	
Panel B: United Kingdom						
	Const	Mkt	Yield	VIX	Illiq.	R^2
RBS	0	-1.84	-1.24^c	-0.01	-0.15	12.52
	(0.05)	(3.28)	(0.71)	(0.01)	(0.20)	
LBG	0.01	-2.81	-0.46^b	-0.01	0	5.74
	(0.03)	(2.29)	(0.21)	(0.01)	(0.06)	
HSBC	0.02	-4.62	-0.85^b	0.03	0.12	17.2
	(0.05)	(4.13)	(0.43)	(0.03)	(0.11)	
SUK	0.02	-3.62^b	-0.39^b	-0.01	0	11.11
	(0.02)	(1.48)	(0.18)	(0.01)	(0.05)	
Barc	0.01	-7.95^c	-1.45^b	-0.02	-0.1	12.05
	(0.06)	(4.68)	(0.61)	(0.02)	(0.14)	
STAN	0.01	-0.33	-1.28^b	0.03	0.03	12.09
	(0.05)	(4.61)	(0.59)	(0.03)	(0.12)	
NW	0.01	-3.36	-0.27	-0.03^b	-0.03	2.46
	(0.03)	(2.11)	(0.20)	(0.01)	(0.05)	

This table reports the regression of weekly changes in the percentage contribution of default risk premia to the 5yr CDS spreads on several variables. The independent variables are the returns on the S&P500 for the US, and the return on the FTSE for the UK (Mkt); the weekly changes in the volatility index for the US and UK (VIX); the weekly changes in the spot 5-yr yield (Yield) for the US and UK; the weekly changes in the measure of illiquidity of Hu, Pan and Wang (2013) (Illiq). The sample consists of weekly observations from January 2, 2008 to July 9, 2013. Newey-West (1987) standard errors are reported in parenthesis. a, b, and c, denote the 1-, 5-, and 10-percent confidence levels, respectively.

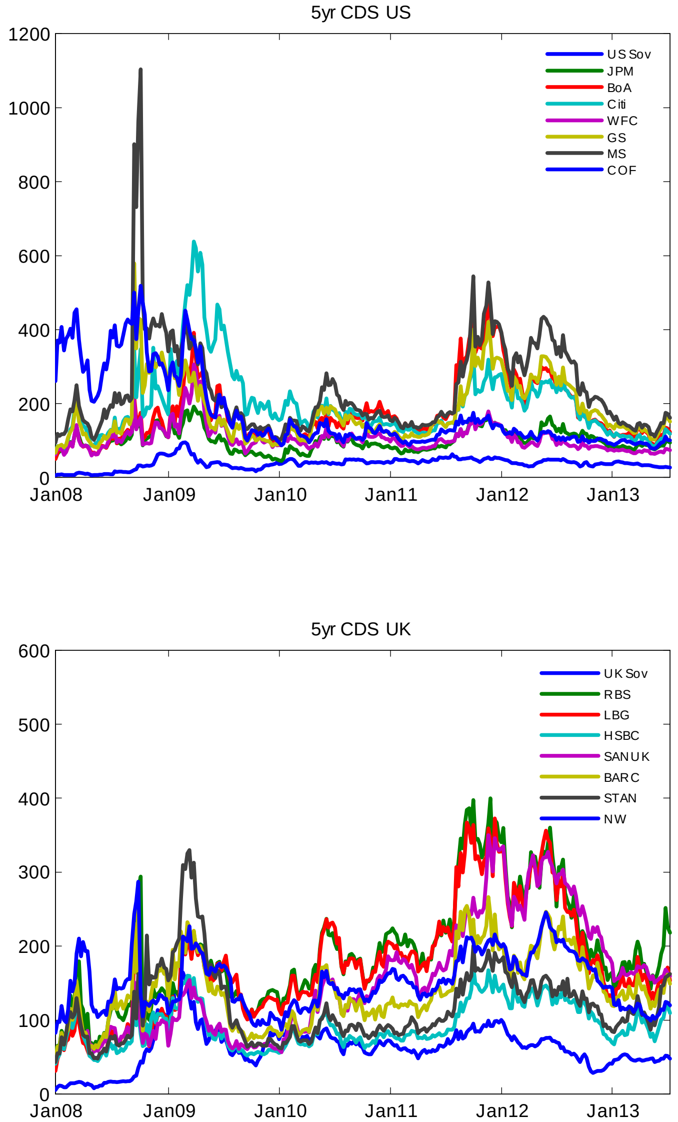
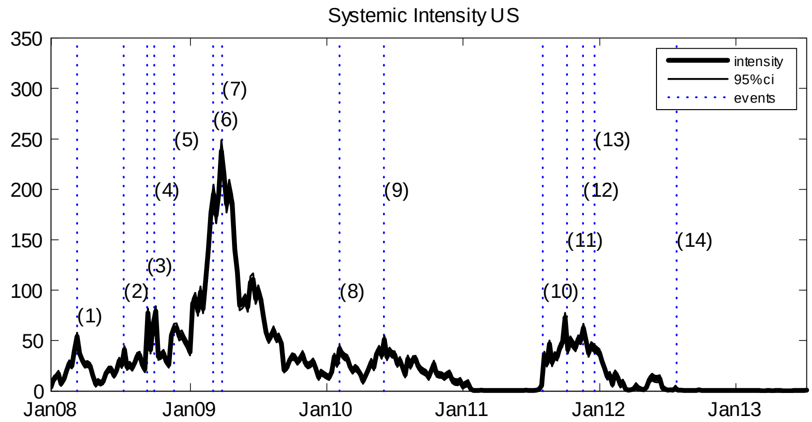


Figure 1: CDS Premia. This figure plots the time series of the five-year sovereign and bank CDS premia (in basis points) for the US and UK. The US banks include: JP Morgan (JPM), Bank of America (BoA), Citi, Wells Fargo & Co (WFC), Goldman Sachs (GS) and Morgan Stanley (MS). The UK banks include: HSBC bank (HSBC), Barclays (BARC), the Royal Bank of Scotland (RBS), Santander UK (SANUK), Lloyds Banking Group (LBG) and Standard Chartered (STAN).



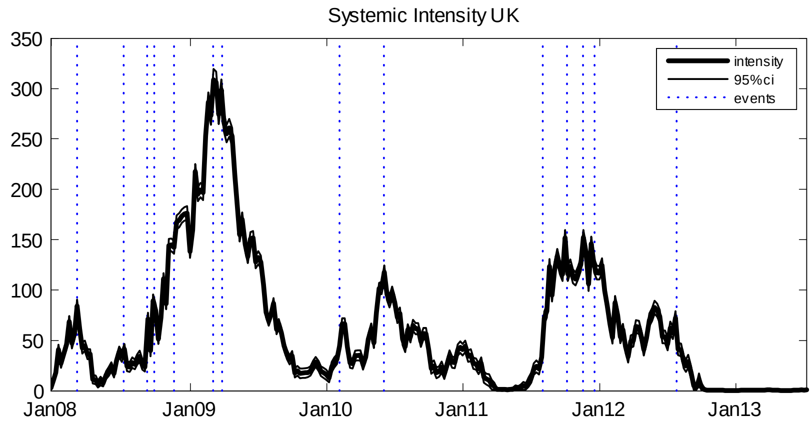
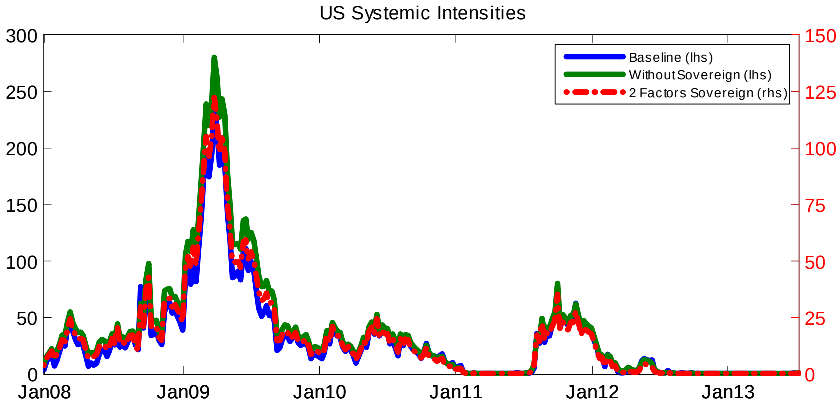


Figure 2: US and UK Bank Systemic Credit Risk. This figure plots the time series of the estimated systemic default intensities (Y_t) and their 95 percent credible intervals. The intensity processes are measured in basis points. Dotted lines are associated with the following selected events; 1) Federal Reserve announces introduction of the TSLF (March-2008); 2) US Treasury announces rescue plan for Fannie Mae and Freddie Mac (July-2008); 3) Lehman Brothers files for bankruptcy (Sep-2008); 4) House of Representatives passes US$700 billion TARP (Oct-2008); 5) FED announces creation of TALF, and a new program to purchase direct obligations of Fannie Mae and Freddie Mac (Nov-2008); 6) US authorities announce launch of the TALF (Mar-2009); 7) G20 Summit communique' announces a trebling of the IMF's available resources to US$750 billion (Apr-2009); 8) first austerity package for Greece (Feb-2010); 9) EFSF is established (Jun-2010); 10) the credit-rating agency Standard & Poor's downgrades the credit rating of US government bond for the first time in the country's history (Aug-2011); 11) the focus shifts on the bigger Italian and Spanish economies (Oct-2011); 12) debt yields across the eurozone increase dramatically (Nov-2011); 13) Euro leaders agree on a new fiscal compact and ECB announces the introduction of the LTRO (Dec-2011); and 14) Speech by Mario Draghi, President of the European Central Bank at the Global Investment Conference in London (July-2012).



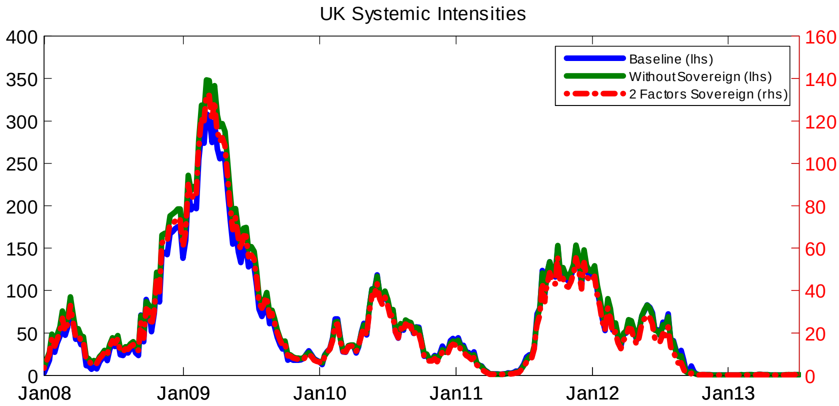


Figure 3: Robustness of Systemic Credit Risk Estimates. This figure plots the time series of the estimated systemic default intensities (Y_t) using three alternative model specifications. The blue line (lhs) is the intensity estimated using the baseline model specification that includes sovereign CDS spreads in the estimation. The green line (lhs) is the estimated intensity resulting from the model estimation where sovereign CDS spreads are excluded from the estimation. In this alternative model specification the systemic exposures for Wells Fargo and HSBC are fixed to 3.04 and 1.00, respectively. These values are the estimated αs resulting from the benchmark model estimation. The red line (rhs) is the systemic intensity resulting from the model specification whereby the sovereign intensity consists of the sum of the systemic intensity and the sovereign-specific intensity. The intensity processes are measured in basis points.

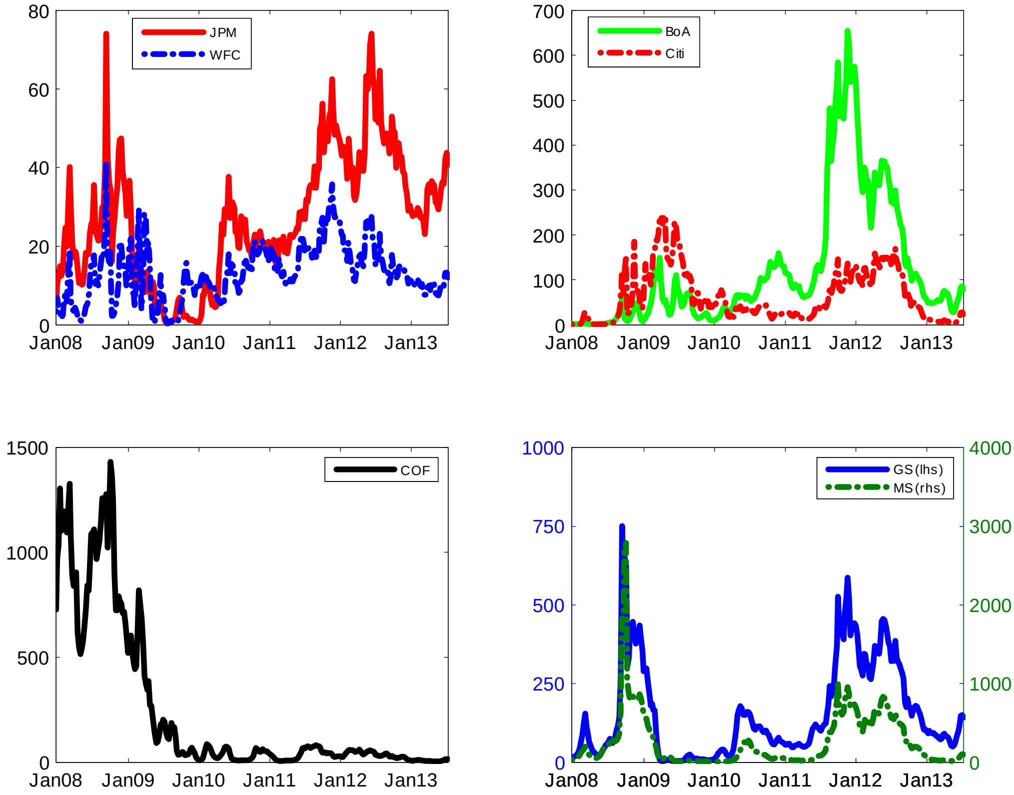


Figure 4: Bank-specific Credit Risk for the US Groups. This figure plots the time series of the US estimated bank-specific default intensities ($X_{i,t}$). Banks are grouped according to their correlation with the first principal component (not reported). The intensity process is measured in basis points.

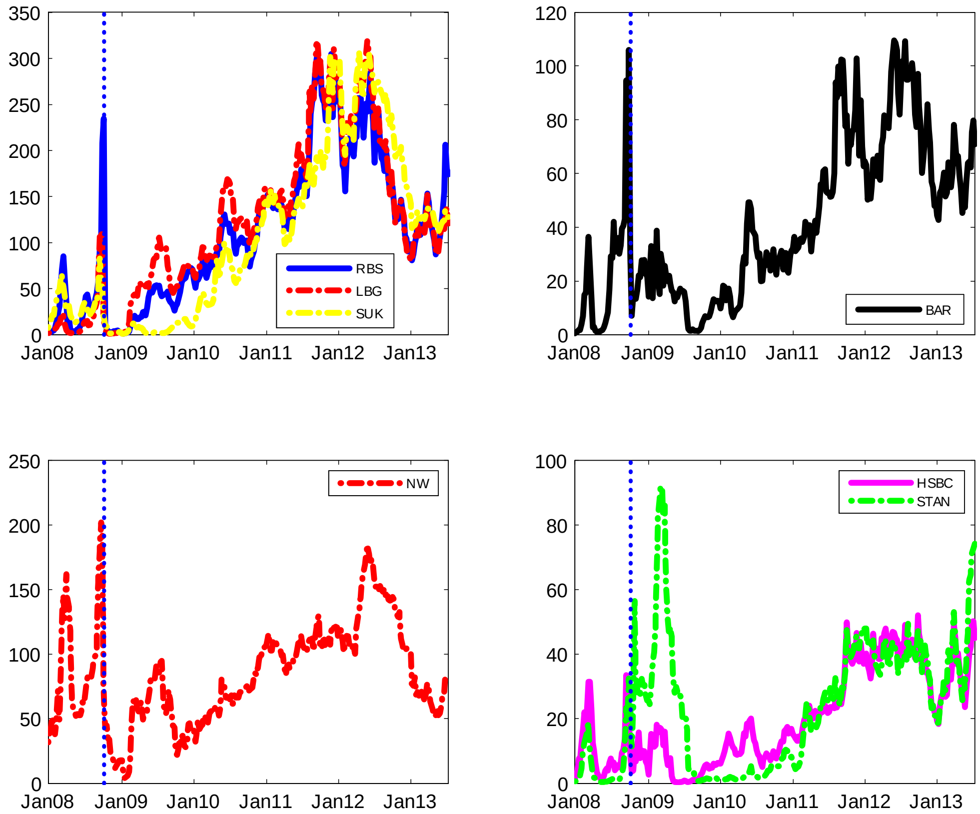


Figure 5: Bank-specific Credit Risk for the UK Groups. This figure plots the time series of the UK estimated bank-specific default intensities ($X_{i,t}$). Banks are grouped according to their correlation with the first principal component (not reported). The intensity process is measured in basis points.

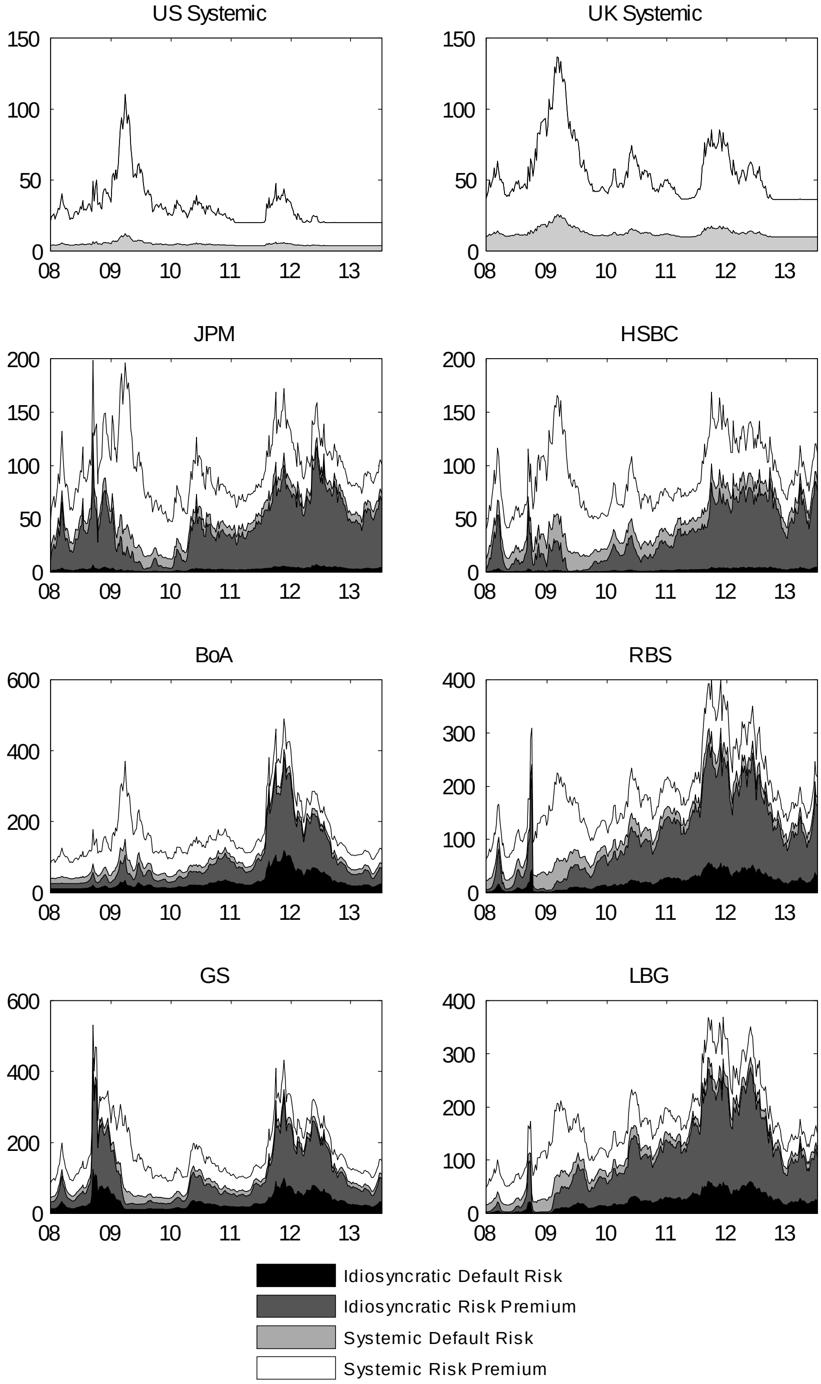


Figure 6: CDS Premia Decomposition for Selected Banks. This figure plots the decomposition of the 3yr bank-specific CDSs. The area named *Idiosyncratic Default Risk* denotes the component of the CDS spread associated with the bank-specific intensity. The area named *Idiosyncratic Risk Premium* denotes the component of the CDS spread associated with the bank-specific risk premium. The area named *Systemic Default Risk* denotes the component of the CDS spread associated with the scaled systemic intensity. The area named *Systemic Risk Premium* denotes the component of the CDS spread associated with the systemic risk premium. A detailed description of the decomposition is provided in the Appendix. CDS spreads are measured in basis points.

Internet Appendix to 'On Bank Credit Risk: Systemic or Bank-Specific? Evidence from the US and UK'

B.1 The US and UK Banking Systems

The US and UK banking systems are regarded as market based. Such systems are generally characterised by bank entities largely relying on funding from other financial institutions, and to a lesser extent from household deposits. As a result, in such systems there is the possibility that banks (and non-bank intermediaries) can become highly interconnected, displaying complex network exposures. Thus, an isolated shock can propagate within the system, leading to a cascade of bank defaults. However, despite these similarities, the US and UK banking systems present significant differences.

A key difference between the US and UK banking systems regards the size of their banking sectors relative to the size of the economy. UK bank assets stand at five times annual GDP as of 2009 (Miles, 2009). In particular, bank assets have increased by tenfold during the past 40 years, with much of the increase reflecting UK banks' oversees business. However, even when excluding foreign currency assets, the size of bank balance-sheets increased fivefold relative to the size of the economy since 1980. In contrast, US bank assets, measured as the size of the top fifty bank holding companies, are about equal to GDP as of 2011.

Table 9 reports the total asset values (in US dollars) for the indicated sample of banks as of 2011. Interestingly, the US and UK banks in our sample are of comparable size. However, the UK banking system is more concentrated than the US. The top six largest UK banks together account for almost 80 percent of the stock of UK customer lending and deposits (Davies et al, 2010). In contrast, the top six largest US banks account for around 60 percent of the total size of the US banking sector as of 2011.[30]

Moreover, the largest UK banks are increasingly regarded as 'universal' banks (Davies et al, 2010). Such transition towards universal banking is reflected in an increase in the contribution of non-interest income to banks' earning. On the other hand, UK banks have experienced an increasing reliance on wholesale funding. In fact, over the 1969-2009 period, retail deposits as a percentage of total liabilities dropped from 88 percent to less than 40 percent. In contrast, US commercial banks have relied less than UK banks on market-based funding, i.e. wholesale funding, as a proportion of their overall funding. However, over the past thirty years, the shadow banking system has become a significant part of the financial system (Adrian and Shin, 2009). As a consequence a number of activities have passed on to a 'parallel banking system', and such institutions, compared to commercial banks, engaged heavily on market-based banking. As a result, wholesale funding rose also in the US.

However, there are also important differences among banks within each banking system. For example, UK banks vary significantly in terms of their business models and geographic footprint, and were accordingly affected differently by the crisis (IMF, 2011). More fundamentally, different business models and geographic footprints can help explain our estimation results. For this reason, we now turn to analysing each bank in turn. Table 9 reports customer deposits and loans as percentage of total assets.[31] We expect commercial banks to substantially rely on deposits for their funding

[30] That said, the US banking system has become more concentrated over time. And, the average size of US banks, relative to GDP has risen roughly by threefold over the past 20 years (Haldane, 2010).

[31] The sources of the data for Table 9 are Bloomberg; individual bank reports; and authors calculations. For the UK we rely also on the "United Kingdom: Stress Testing the Banking Sector Technical Note" published by the International Monetary Fund on July 2011.

and on loans for their activities. For example, Barclays and RBS rely little on deposits and loans, whereas Santander UK and LBG loans are larger than 60 percent and their funding through deposits is also remarkable. Standard Chartered strongly relies on deposits, but loans are less than 45 percent of their total assets. HSBC does a substantial amount of its funding through deposits, though its activities are more oriented towards investment banking similarly to Barclays and RBS. Nationwide is a building-society and major provider of mortgage loans and savings. In fact, it displays the highest reliance on loans (78 percent). Table 9 also reports the geographic footprint, i.e. the regional split of bank revenues. A large share of HSBC and Standard Chartered revenues stems from their Asian activities. In fact Standard Chartered share of domestic revenues is negligible. In contrast, Santander UK, LBG and Nationwide activities are concentrated in the UK. Finally, Barclays, HSBC and RBS display significant exposures to the US and Europe.

As for the US, Wells Fargo and Capital One have more of a retail focus than any other US banks included in our sample.[32] Then, Bank of America, Citi and JP Morgan follow, displaying a substantial share of deposits and loans. By contrast, Goldman Sachs and Morgan Stanley strongly rely on wholesale funding and on investment banking activities. In sum, the business model analysis suggests the presence of three distinct groups; the first includes Wells Fargo and Capital One, the second Citi, Bank of America and JP Morgan, and the third Goldman Sachs and Morgan Stanley. As for the geographic footprint, Citi stands out as being the most international bank in our sample. In fact, less than 30 percent of its revenues stem from their domestic activities, whereas the rest is almost equally split across the other regions. Also, a significant share of Goldman Sachs and Morgan Stanley revenues are located in Europe, and a lower but still significant share is located in Asia. JP Morgan share of European revenues is also large, but its share of Asian revenues is small. That said, the larger share of JP Morgan revenues is domestic. Bank of America has an even larger focus on the domestic market, with a share of domestic revenues around 82 percent, whereas the remaining share of revenues is almost equally split between Europe and Asia. But Wells Fargo and Capital One retain the largest share of domestic revenues.

C MCMC Implementations

Bayesian estimation tries to find the posterior distribution of parameters and states given the whole set of observations, $p(\Theta, H|y)$, where Θ denotes the parameters, H denotes the latent states (i.e. the systemic and the N bank-specific default intensities), and $y = y_{1:T}$ denotes the data ($\mathrm{CDS}^{obs}_{1:T}$). Direct sampling from the posterior distribution $p(\Theta, H|y)$ is often not feasible due to its high dimensionality or complicated form. The Markov Chain Monte Carlo (MCMC) method solves the problem of simulating from this complicted target distribution by simulating from simpler conditional distributions. Precisely, by applying the Bayes' rule, the posterior density can be decomposed as follows

$$p(\Theta, H|y) \propto p(y|H, \Theta)p(H|\Theta)p(\Theta), \tag{C.1}$$

where $p(y|H, \Theta)$ is the likelihood function given the states and the parameters, $p(H|\Theta)$ is the probability distribution of states conditional on the parameters, and $p(\Theta)$ is the prior density of the parameters. We can then iteratively draw from the full conditionals $p(\Theta|H, y)$ and $p(H|\Theta, y)$. The

[32] The data of these paragraph on the US banks are from Bloomberg. In particular, we use balance-sheet data on total assets, loans and mortgages, customer deposits, and net revenues by geographic region. The statistics refer to the average over the 2008-11 period.

parameter set Θ and the state set H can be further broken into smaller blocks. Next we derive the conditional distributions for each block.

C.1 The Posterior Distributions

Step 1: Draw Mean Reversion Parameters ($\kappa_{1,Y}^{\mathbb{P}}$ and $\kappa_{1,i}^{\mathbb{P}}$)

The parameters $\kappa_{1,Y}^{\mathbb{P}}$ and $\kappa_{1,i}^{\mathbb{P}}, i = 1, \ldots, N$, only enter the respective objective dynamics. Therefore, we have, for $\kappa_{1,Y}^{\mathbb{P}}$,

$$\begin{aligned} p(\kappa_{1,Y}^{\mathbb{P}} | y_{1:T}, Y_{1:T}, X_{1:T}, \Theta_-) &\propto p(Y_{1:T} | \kappa_{1,Y}^{\mathbb{P}}, \Theta_-) p(\kappa_{1,Y}^{\mathbb{P}}) \\ &\propto \exp\left(-\frac{1}{2}\sum_{t=1}^{T} \frac{(Y_t - \kappa_{0,Y}\tau - (1-\kappa_{1,Y}^{\mathbb{P}}\tau)Y_{t-1})^2}{\sigma_Y^2 \tau Y_{t-1}}\right) p(\kappa_{1,Y}^{\mathbb{P}}) \\ &\propto \exp\left(-\frac{1}{2}\sum_{t=1}^{T} \frac{(a_t \kappa_{1,Y}^{\mathbb{P}} - b_t)^2}{\sigma_Y^2 \tau Y_{t-1}}\right) p(\kappa_{1,Y}^{\mathbb{P}}), \end{aligned} \tag{C.2}$$

where $a_t = \tau Y_{t-1}$ and $b_t = \kappa_{0,Y}\tau + Y_{t-1}$. Given a flat prior, the posterior distribtion is a normal $\kappa_{1,Y}^{\mathbb{P}} \to N(Qm, \mathbb{Q})$, where $m = \sum_{t=1}^{T} \frac{a_t b_t}{\sigma_Y^2 \tau Y_{t-1}}$ and $\mathbb{Q}^{-1} = \sum_{t=1}^{T} \frac{a_t^2}{\sigma_Y^2 \tau Y_{t-1}}$. Similar results hold for $\kappa_{1,i}^{\mathbb{P}}$, for $i = 1, \ldots, N$.

Step 2: Draw Measurement Error Variance ($\sigma_{i,\epsilon}^2$)

For each entity i, $i = 0, 1, \ldots, N$, we assume normal measurement errors with constant variance $\sigma_{i,\epsilon}^2$, that is, $\Sigma_{i,\epsilon} = \sigma_{i,\epsilon}^2 I_M$, where I denotes the identity matrix and M is the number of maturities. Therefore, we have

$$\begin{aligned} p(\sigma_{i,\epsilon}^2 | y_{i,1:T}, Y_{1:T}, X_{i,1:T}, \Theta_-) &\propto p(y_{i,1:T} | \sigma_{i,\epsilon}^2, Y_{1:T}, X_{i,1:T}, \Theta_-) p(\sigma_{i,\epsilon}^2) \\ &\propto |\Sigma_{i,\epsilon}|^{-T/2} \exp\left[-\frac{1}{2}\sum_{t=1}^{T} \hat{e}_{i,t}' \Sigma_{i,\epsilon}^{-1} \hat{e}_{i,t}\right] p(\sigma_{i,\epsilon}^2), \end{aligned} \tag{C.3}$$

where $\hat{e}_{i,t}$ is the pricing error $y_{i,t} - CDS_i(t, T; Y_t, X_{i,t}, \Theta)$, and $\Sigma_{i,\epsilon}$ denotes the variance-covariance matrix of measurement errors. Thus, $\sigma_{i,\epsilon}^{-2}$ has a inverse Gamma distribution $IG(a, b)$, where $a = \frac{T}{2}M$ and $b = \sum_{t=1}^{T} \hat{e}_{i,t}\hat{e}_{i,t}'$, given the flat prior.

Step 3: Draw Parameters (κ_0 and σ)

The parameters κ_0 and σ are sampled by the slice sampling method as their posterior distributions are not known. Note that the parameters $\kappa_{0,Y}/\sigma_Y$ and $\kappa_{0,i}/\sigma_i$ enter into both the pricing formula and the respective objective dynamics. Thus, we have, for $\kappa_{0,Y}/\sigma_Y$,

$$\begin{aligned} p(\kappa_{0,Y}, \sigma_Y | y_{1:T}, Y_{1:T}, X_{1:T}, \Theta_-) &\propto \prod_{t=1}^{T} p(y_t|Y_t, X_t, \Theta) p(Y_t|Y_{t-1}, \kappa_{0,Y}, \sigma_Y) p(\kappa_{0,Y}, \sigma_Y) \\ &\propto \frac{1}{\sigma_Y^T} \exp\left[-\frac{1}{2} \sum_{t=1}^{T} \left(\hat{e}_t' \Sigma_\epsilon^{-1} \hat{e}_t + \frac{A_{Y,t}}{\sigma_Y^2 \tau Y_{t-1}} \right) \right] p(\kappa_{0,Y}, \sigma_Y), \end{aligned} \tag{C.4}$$

where $A_{Y,t} = (Y_t - \kappa_{0,Y}\tau - (1-\kappa_{1,Y}^{\mathbb{P}}\tau)Y_{t-1})^2$. Similar results can be found for $\kappa_{0,i}/\sigma_i$, for $i = 1, \ldots, N$. But now they only enter into bank i's CDS pricing.

Step 4: Draw Risk-neutral Parameters ($\kappa_1^{\mathbb{Q}}$ and α)

The parameters $\kappa_1^{\mathbb{Q}}$ and α are sampled by the slice sampling method as their conditional distributions are not known. Note that the parameters $\kappa_1^{\mathbb{Q}}$ and α only enter into the pricing formula. Therefore, we have, for $\kappa_{1,i}^{\mathbb{Q}}$ and α_i, $i = 1, \ldots, N$,

$$\begin{aligned} p(\kappa_{1,i}^{\mathbb{Q}}, \alpha_i | y_{i,1:T}, Y_{1:T}, X_{i,1:T}, \Theta_-) &\propto \prod_{t=1}^{T} p(y_{i,t}|Y_t, X_{i,t}, \Theta) p(\kappa_{1,i}^{\mathbb{Q}}, \alpha_i) \\ &\propto \exp\left[-\frac{1}{2} \sum_{t=1}^{T} \hat{e}_{i,t}' \Sigma_{i,\epsilon}^{-1} \hat{e}_{i,t} \right] p(\kappa_{1,i}^{\mathbb{Q}}, \alpha_i), \end{aligned} \tag{C.5}$$

and for $\kappa_{1,Y}^{\mathbb{Q}}$ (α_Y is fixed at one),

$$\begin{aligned} p(\kappa_{1,Y}^{\mathbb{Q}} | y_{1:T}, Y_{1:T}, X_{1:T}, \Theta_-) &\propto \prod_{t=1}^{T} p(y_t|Y_t, X_t, \Theta) p(\kappa_{1,Y}^{\mathbb{Q}}) \\ &\propto \exp\left[-\frac{1}{2} \sum_{t=1}^{T} \hat{e}_t' \Sigma_\epsilon^{-1} \hat{e}_t \right] p(\kappa_{1,Y}^{\mathbb{Q}}). \end{aligned} \tag{C.6}$$

Step 5: Draw Systemic Intensity ($\mathbf{Y}_t$)

The latent state Y_ts are sampled individually by the slice sampling method. For $t = 1, \ldots, T$, the conditional posterior is

$$\begin{aligned} p(Y_t | y_{1:T}, X_{1:T}, Y_{-t}, \Theta) &\propto p(y_t|Y_t, X_t, \Theta) p(Y_t|Y_{t+1}, Y_{t-1}, \Theta) \\ &\propto p(y_t|Y_t, X_t, \Theta) p(Y_{t+1}|Y_t, \Theta) p(Y_t|Y_{t-1}, \Theta), \end{aligned} \tag{C.7}$$

where the first term in (C.7) denotes the conditional likelihood,

$$\begin{aligned} p(y_t|Y_t, X_t, \Theta) &\propto \exp\left[-\frac{1}{2}\left(y_t - CDS(t,T;Y_t,X_t,\Theta)\right)' \Sigma_\epsilon^{-1}\left(y_t - CDS(t,T;Y_t,X_t,\Theta)\right)\Big)\right] \\ &\propto \exp\left[-\frac{1}{2}\hat{e}_t'\Sigma_\epsilon^{-1}\hat{e}_t\right]. \end{aligned} \tag{C.8}$$

The second and third terms are given by

$$p(Y_{t+1}|Y_t, \Theta) \propto \frac{1}{\sigma_Y\sqrt{\tau Y_t}}\exp\left(-\frac{1}{2}\frac{(Y_{t+1} - \kappa_{0,Y}\tau - (1-\kappa_{1,Y}^{\mathbb{P}}\tau)Y_t)^2}{\sigma_Y^2\tau Y_t}\right), \tag{C.9}$$

$$p(Y_t|Y_{t-1}, \Theta) \propto \exp\left(-\frac{1}{2}\frac{(Y_t - \kappa_{0,Y}\tau - (1-\kappa_{1,Y}^{\mathbb{P}}\tau)Y_{t-1})^2}{\sigma_Y^2\tau Y_{t-1}}\right). \tag{C.10}$$

For Y_T the conditional posterior is

$$p(Y_T|y_{1:T}, X_{1:T}, Y_{-T}, \Theta) \propto p(y_T|Y_T, X_T, \Theta)p(Y_T|Y_{T-1}, \Theta), \tag{C.11}$$

and, similarly, for Y_0 is

$$p(Y_0|y_{1:T}, X_{1:T}, Y_{-0}, \Theta) \propto p(y_0|Y_0, X_0, \Theta)p(Y_0|Y_1, \Theta), \tag{C.12}$$

Step 6: Draw Bank-specific Intensity ($\mathbf{X}_{i,t}$)

The latent state $X_{i,t}$ are sampled individually by the slice sampling method. For $i = 1, \ldots, N$ and $t = 1, \ldots, T$, the conditional posterior is

$$\begin{aligned} p(X_{i,t}|y_{i,1:T}, X_{i,-t}, Y_{1:T}, \Theta) &\propto p(y_{i,t}|Y_t, X_{i,t}, \Theta)p(X_{i,t}|X_{i,t+1}, X_{i,t-1}, \Theta) \\ &\propto p(y_{i,t}|Y_t, X_{i,t}, \Theta)p(X_{i,t+1}|X_{i,t}, \Theta)p(X_{i,t}|X_{i,t-1}, \Theta), \end{aligned} \tag{C.13}$$

where the first term in (C.13) is

$$\begin{aligned} p(y_{i,t}|Y_t, X_{i,t}, \Theta) &\propto \exp\left[-\frac{1}{2}\left(y_{i,t} - CDS_i(t,T;Y_t,X_{i,t},\Theta)\right)' \Sigma_{i,\epsilon}^{-1}\left(y_t - CDS_i(t,T;Y_t,X_{i,t},\Theta)\right)\right], \\ &\propto \exp\left[-\frac{1}{2}\hat{e}_{i,t}'\Sigma_{i,\epsilon}^{-1}\hat{e}_{i,t}\right], \end{aligned} \tag{C.14}$$

the second and third terms are given by

$$p(X_{i,t+1}|X_{i,t}, \Theta) \propto \frac{1}{\sigma_Y\sqrt{\tau X_{i,t}}}\exp\left(-\frac{1}{2}\frac{(X_{i,t+1} - \kappa_{0,Y}\tau - (1-\kappa_{1,Y}^{\mathbb{P}}\tau)X_{i,t})^2}{\sigma_Y^2\tau X_{i,t}}\right), \tag{C.15}$$

$$p(X_{i,t}|X_{i,t-1}, \Theta) \propto \exp\left(-\frac{1}{2}\frac{(X_{i,t} - \kappa_{0,Y}\tau - (1-\kappa_{1,Y}^{\mathbb{P}}\tau)X_{i,t-1})^2}{\sigma_Y^2\tau X_{i,t-1}}\right). \tag{C.16}$$

For $X_{i,T}$ the conditional posterior is

$$p(X_{i,T}|y_{i,1:T}, X_{i,-T}, Y_{1:T}, \Theta) \propto p(y_T|Y_T, X_{i,T}, \Theta)p(X_{i,T}|X_{i,T-1}, \Theta), \tag{C.17}$$

and, similarly, for $X_{i,0}$ is

$$p(X_{i,0}|y_{i,1:T}, X_{i,-0}, Y_{1:T}, \Theta) \propto p(y_0|Y_0, X_{i,0}, \Theta)p(X_{i,0}|X_{i,1}, \Theta), \tag{C.18}$$

C.2 Implementation Details and Slice Sampler

The priors used in this study are diffuse, and their distributions are chosen for convenience using a number of earlier papers (e.g. Johannes and Polson, 2009). By repeatedly simulating from the conditional distribution of each block in turn we get samples of draws. These draws, beyond a burn-in period, are treated as variates from the target posterior distribution. More specifically, we perform 100,000 replications of which the first 50,000 are burned-in, and we save 1 every 10 draws of the last 50,000 replications of the chan so that the draws are independent.

We mainly use the slice sampling method recently developed by Neal (2003) when sampling from the non-standard distributions. The method is based on the observation that to sample a random variable, one can sample uniformly from the region under the curve of its probability density function. A Markov chain that converges to this uniform distribution can be constructed by alternately sampling uniformly from the vertical interval defined by the density at the current point and from the union of intervals that constitutes the horizontal slices. Slice sampling method can adaptively change the scale in choosing slice, which makes it easier to tune than the Metropolis-Hastings algorithm and other methods and avoids problems arising when the appropriate scale of changes varies over time (Neal, 2003). This adaptive property is particularly suitable to draw samples for state estimation.

Slice sampler works with the following steps for a given posterior distribution $p(x)$:

- *Step 1:* Starting from an initial value x_0, uniformly draw a real value y from $(0, p(x_0))$;
- *Step 2:* Find an interval around x_0, that contains all, or most of the slices $S = \{x : y < p(x)\}$;
- *Step 3:* Uniformly draw a new point x from the part of the slice within this interval as a sample from the distribution $p(x)$;
- *Step 4:* Take x as a new starting value, and repeat Step 1-3.

C.3 Distress Risk Premia

In this section, we review the algebra to compute the distress risk premia and decompose CDS spreads. Following Pan and Singleton (2008) the distress risk premia are given by the difference of the CDS price under the risk-neutral measure and the CDS price under the objective measure.

We reapeat for convenience the risk-neutral price of the CDS:

$$CDS(t,T) = \frac{(1-R^{\mathbb{Q}})E^{\mathbb{Q}}\Big[\int_t^T \lambda_{i,s}\exp\Big(-\int_t^s r_u + \lambda_{i,u}du\Big)ds\Big]}{E^{\mathbb{Q}}\Big[\int_t^T \exp\Big(-\int_t^s r_u + \lambda_{i,u}du\Big)ds\Big]}. \tag{C.19}$$

which in compact form is $CDS(t,T) = s(t,T;Y_t,X_{i,t},\alpha_i,\kappa_0,\kappa_{0,i},\kappa_1^{\mathbb{Q}},\kappa_{1,i}^{\mathbb{Q}},\sigma_i,\sigma)$, where $s(\cdot)$ denotes the pricing function (i.e. the non-linear mapping of the intensities into the CDS spread given by eq. (A.3)).

The pseudo-objective price of the CDS is

$$CDS^{\mathbb{P}}(t,T) = \frac{(1-R^{\mathbb{Q}})E^{\mathbb{P}}\Big[\int_t^T \lambda_{i,s}\exp\Big(-\int_t^s r_u + \lambda_{i,u}du\Big)ds\Big]}{E^{\mathbb{P}}\Big[\int_t^T \exp\Big(-\int_t^s r_u + \lambda_{i,u}du\Big)ds\Big]}, \tag{C.20}$$

which in compact form is $CDS^{\mathbb{P}}(t,T) = s(t,T;Y_t,X_{i,t},\alpha_i,\kappa_0,\kappa_{0,i},\kappa_1^{\mathbb{P}},\kappa_{1,i}^{\mathbb{P}},\sigma_i,\sigma)$, whereby the change of expectation consists of setting the market price of risk to zero. Given our essentially affine specification of the market price of risk, this implies that pseudo-objective price of the CDS spread is obtained by replacing $\kappa_1^{\mathbb{Q}}$ with $\kappa_1^{\mathbb{P}}$.

Accordingly, the time t percentage contribution of the distress risk premium to spread with maturity T is computed as:

$$CRP(t,T) = \frac{\big[CDS(t,T) - CDS^{\mathbb{P}}(t,T)\big]}{CDS(t,T)}. \tag{C.21}$$

So far we have dealt with the total distress risk premium, which consists of the sum of the scaled systemic risk premium and the idiosyncratic risk premium. In principle, we would like to separate these two distinct risk premia. We compute the systemic distress risk premium for bank i as:

$$SCRP(t,T) = \frac{\big[CDS(t,T) - CDS^{Y,\mathbb{P}}(t,T)\big]}{CDS(t,T)}, \tag{C.22}$$

whereby $CDS^{Y,\mathbb{P}}(t,T) = s(t,T;Y_t,X_{i,t},\alpha_i,\kappa_0,\kappa_{0,i},\kappa_1^{\mathbb{P}},\kappa_{1,i}^{\mathbb{Q}},\sigma_i,\sigma)$, thus by replacing $\kappa_1^{\mathbb{Q}}$ with $\kappa_1^{\mathbb{P}}$. Similarly, we compute the idiosyncratic distress risk premia as:

$$ICRP(t,T) = \frac{\big[CDS(t,T) - CDS^{X,\mathbb{P}}(t,T)\big]}{CDS(t,T)}, \tag{C.23}$$

whereby $CDS^{X,\mathbb{P}}(t,T) = s(t,T;Y_t,X_{i,t},\alpha_i,\kappa_0,\kappa_{0,i},\kappa_1^{\mathbb{Q}},\kappa_{1,i}^{\mathbb{P}},\sigma_i,\sigma)$, thus by replacing $\kappa_{1,i}^{\mathbb{Q}}$ with $\kappa_{1,i}^{\mathbb{P}}$.

By a similar argument we can decompose the CDS spread into the following four components: i) bank-specific credit risk; ii) bank-specific distress risk premium; iii) systemic credit risk; iv) systemic distress risk premium. We first compute the pseudo-objective and risk-neutral CDS spreads assuming that bank i has no systemic risk exposure (i.e. $\alpha_i = 0$).[33] Precisely,

$$\begin{aligned} ICDS^{\mathbb{P}}(t,T) &= s(t,T;Y_t,X_{i,t},0,\kappa_0,\kappa_{0,i},\kappa_1^{\mathbb{Q}},\kappa_{1,i}^{\mathbb{P}},\sigma_i,\sigma), && \text{(C.24)} \\ ICDS^{\mathbb{Q}}(t,T) &= s(t,T;Y_t,X_{i,t},0,\kappa_0,\kappa_{0,i},\kappa_1^{\mathbb{Q}},\kappa_{1,i}^{\mathbb{Q}},\sigma_i,\sigma), && \text{(C.25)} \end{aligned}$$

where $ICDS^{\mathbb{P}}$ denotes the part of the CDS associated with idiosyncratic credit risk, whereas $\big[ICDS^{\mathbb{Q}} - ICDS^{\mathbb{P}}\big]$ the part associated with the idiosyncratic distress risk premium. Systemic credit risk is then computed as $\big[CDS^{Y,\mathbb{P}} - ICDS^{\mathbb{Q}}\big]$, and systemic risk premium as $\big[CDS - CDS^{Y,\mathbb{P}}\big]$.

[33] This effectively consists of pricing the CDS using a one-factor model.

Table 9: Business Models and Geographic Footprint

Panel A: United States								
	Business Model			Geographic Footprint				
	Total Assets	Deposits	Loans	Domestic	LatAm	Europe	Asia	RoW
JPM	2,359,141	46.6	32.5	75.9	2	16	5.7	0.5
BoA	2,209,974	46.4	43.8	81.9	3.3	7.5	7.3	-
Citi	1,864,660	44.8	35.9	28.6	15.9	15.9	17.8	21.8
WFC	1,422,968	65.8	61.9	100	-	-	-	-
GS	938,555	26.9	8.7	59.3	-	25.9	14.9	-
MS	780,960	23.7	5.2	67.9	-	21.3	10.8	-
COF	312,918	62.1	58.5	93.0	n/a	n/a	n/a	n/a

Panel B: United Kingdom								
	Business Model			Geographic Footprint				
	Total Assets	Deposits	Loans	Domestic	USA	Europe	Asia	RoW
HSBC	2,692,500	48	38.5	26.2	23	9.5	29.1	12.2
Barc	2,420,600	21.2	27.6	41.4	23	14.9	4.6	16.1
RBS	2,131,400	28	36.1	60.9	17.6	16	n/a	5.5
SANUK	475,962	48.7	65	100	-	-	-	-
LBG	1,501,700	40.4	60.8	94	0.4	4.6	1	-
STAN	636,518	57.1	44.6	2.6	5.1	2.6	69.4	20.3
NW	311,433	63.9	78.8	100	-	-	-	-

The table reports bank-by-bank statistics on the Business Model and Geographic Footprint for the indicated US and UK banks. The *Business Model* panel (left) includes; total asset values as of 2012-Q4 (measured in millions of US dollars); customer deposits over total assets for the 2008-11 period (deposits); loans over total assets for the 2008-11 period (loans). For Capital One due to data availability deposits is the 2010-11 average. The *Geographic Footprints* panel (right) presents revenues by geographical location as percentage of total revenues for the 2008-2011 period. n/a denotes data not available. Sources: Bloomberg; individual bank reports; and author calculations.

Table 10: Alternative Model Specification: Pricing Errors

	United States				United Kingdom		
	5yr	7yr	10yr		5yr	7yr	10yr
Sov	9.9	5.8	8.7	Sov	11.1	7.5	9.8
JPM	4.7	4.2	6.2	RBS	3.7	4.3	5.5
BoA	8.4	9.0	12.1	LBG	4.4	5.1	6.5
Citi	3.9	3.7	5.6	HSBC	5.1	2.9	4.2
WFC	3.5	3.4	6.0	SUK	4.6	3.6	5.1
GS	6.5	8.5	11.8	Barc	3.6	3.0	4.4
MS	9.4	12.6	15.8	STAN	4.7	3.1	3.7
COF	6.4	7.2	8.8	N	4.0	3.1	4.0

The table reports the mean absolute percentage pricing errors (MAPPE) for the CDS spreads of the indicated maturities resulting from the alternative model specification whereby the sovereign's intensity composes of a systemic factor (Y_t) and a sovereign-specific factor ($X_{0,t}$), i.e. $\lambda_{0,t} = Y_t + X_{0,t}$. Left panel reports results for the United States and right panel for the United Kingdom. The model is estimated over the period from January 2 2008 to July 9 2013.

Table 11: The Term Structure of US Risk Premia Components

	Systemic Risk Premia								
	3-year			5-year			10-year		
	Mean	Med.	SDev	Mean	Med.	SDev	Mean	Med.	SDev
JPM	47	46	17	46	43	17	45	42	15
BoA	41	38	18	40	39	15	38	38	11
Citi	49	50	10	46	47	10	43	44	8
WFC	57	56	11	54	51	11	51	50	9
GS	36	34	17	37	36	15	36	37	11
MS	33	34	14	33	35	12	34	35	8
COF	33	33	12	35	36	10	36	37	7
	Bank-specific Risk Premia								
	3-year			5-year			10-year		
	Mean	Med.	SDev	Mean	Med.	SDev	Mean	Med.	SDev
JPM	34	35	17	41	44	18	44	47	16
BoA	24	25	13	31	30	14	40	38	12
Citi	24	23	12	32	31	13	38	37	11
WFC	22	24	11	31	33	12	36	37	11
GS	29	30	13	35	36	13	41	40	12
MS	29	26	11	33	30	11	37	34	8
COF	25	21	9	29	25	9	33	30	7
	Total Risk Premia								
	3-year			5-year			10-year		
	Mean	Med.	SDev	Mean	Med.	SDev	Mean	Med.	SDev
JPM	81	81	2	87	87	2	90	91	2
BoA	65	64	5	72	71	2	78	78	1
Citi	73	74	3	78	78	3	82	81	3
WFC	79	79	2	85	85	2	88	88	2
GS	65	64	5	72	72	2	78	78	1
MS	62	61	4	67	67	3	71	71	2
COF	58	56	5	64	63	3	68	68	2

This table reports summary statistics for the term structure of the percentage contribution of default risk premia to the 3-, 5-, and 10-year spreads for the US, as described in section 7.1. Top panel (*Systemic Risk Premia*) denotes the default risk premia attached to the scaled systemic intensity ($\alpha_i Y_t$). Centre panel (*Bank-specific Risk Premia*) denotes the default risk premia attached to the bank-specific intensity ($X_{i,t}$). Bottom panel (*Total Risk Premia*) denotes default risk premia attached to the sum of the systemic and bank-specific intensities ($\lambda_{i,t} = \alpha_i Y_t + X_{i,t}$).

Table 12: The Term Structure of UK Risk Premia Components

	Systemic Risk Premia								
	3-year			5-year			10-year		
	Mean	Med.	SDev	Mean	Med.	SDev	Mean	Med.	SDev
RBS	35	30	17	37	31	18	39	34	17
LBG	33	26	19	35	28	19	37	30	19
HSBC	48	50	15	49	50	16	52	52	16
SUK	34	28	21	36	30	22	39	33	21
Barc	45	45	15	46	44	16	47	46	15
STAN	54	58	12	56	58	13	56	53	15
NW	34	32	13	36	34	12	38	36	10
	Bank-specific Risk Premia								
	3-year			5-year			10-year		
	Mean	Med.	SDev	Mean	Med.	SDev	Mean	Med.	SDev
RBS	32	38	16	40	45	18	44	49	19
LBG	34	40	16	41	49	19	46	54	21
HSBC	27	25	17	33	33	18	35	35	18
SUK	35	40	19	41	48	22	45	51	22
Barc	28	29	16	35	36	18	37	38	18
STAN	17	15	13	22	23	16	27	31	18
NW	37	38	12	43	45	12	46	48	11
	Total Risk Premia								
	3-year			5-year			10-year		
	Mean	Med.	SDev	Mean	Med.	SDev	Mean	Med.	SDev
RBS	68	68	2	77	77	2	84	84	2
LBG	67	66	3	77	77	1	84	85	2
HSBC	75	76	3	83	83	3	87	87	3
SUK	69	68	3	78	78	1	85	86	2
Barc	73	74	3	81	81	3	85	85	3
STAN	71	71	3	78	79	3	83	84	4
NW	71	70	2	79	79	1	85	85	1

This table reports summary statistics for the term structure of the percentage contribution of default risk premia to the 3-, 5-, and 10-year spreads for the UK, as described in section 7.1. Top panel (*Systemic Risk Premia*) denotes the default risk premia attached to the scaled systemic intensity ($\alpha_i Y_t$). Centre panel (*Bank-specific Risk Premia*) denotes the default risk premia attached to the bank-specific intensity ($X_{i,t}$). Bottom panel (*Total Risk Premia*) denotes default risk premia attached to the sum of the systemic and bank-specific intensities ($\lambda_{i,t} = \alpha_i Y_t + X_{i,t}$).

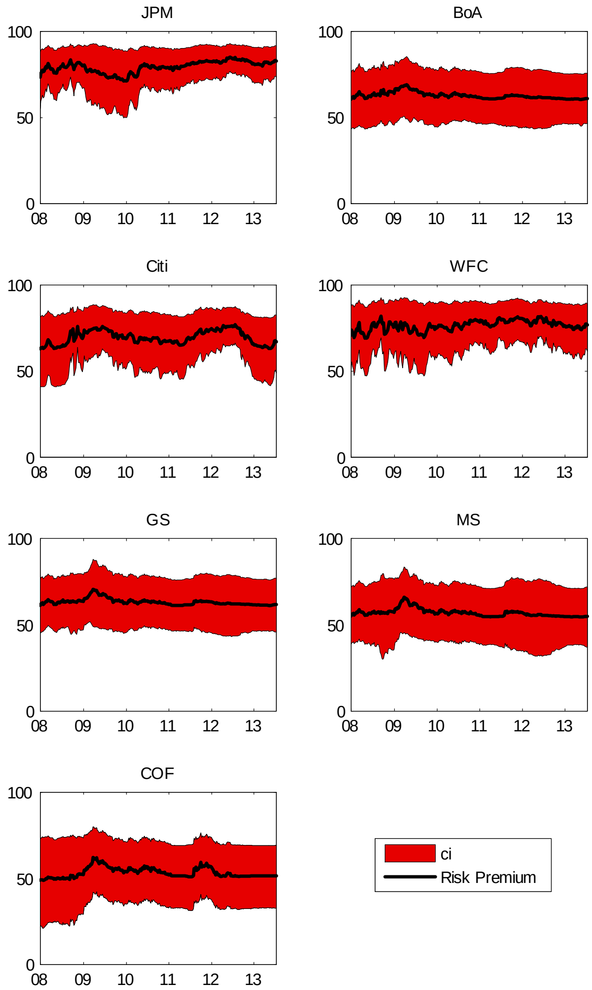


Figure A.1: US Total Risk Premia. This figure plots the time series of the percentage contribution of the total default risk premium to the 5-year CDS spread (in percentage) as described in section 7.1. The red area denotes the (27-68) Bayesian confidence intervals. The US banks include: JP Morgan (JPM), Bank of America (BoA), Citi, Wells Fargo & Co (WFC), Goldman Sachs (GS), Morgan Stanley (MS) and Capital One Financial (COF).

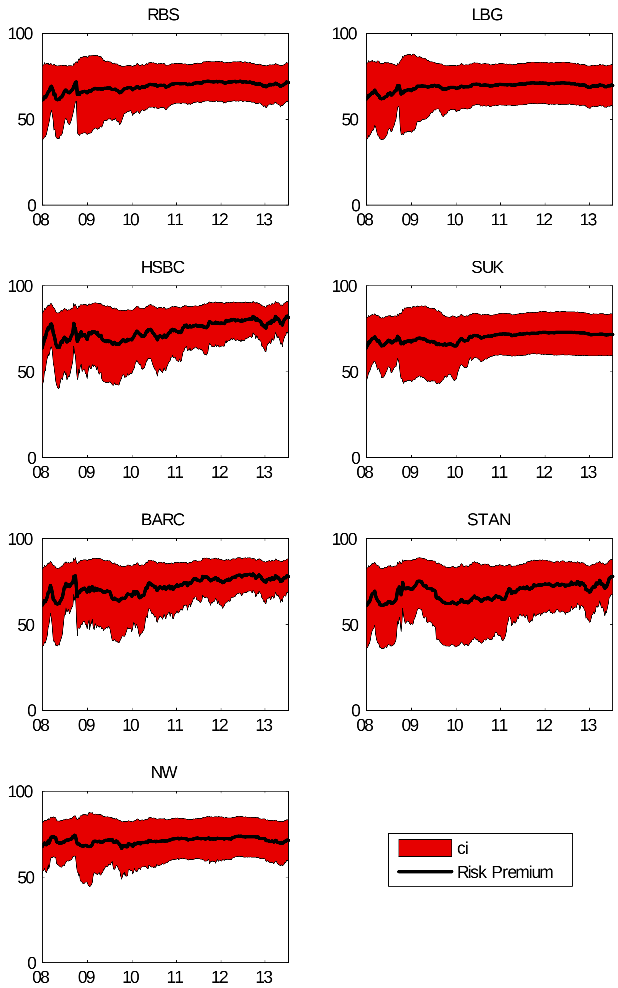


Figure A.2: UK Total Risk Premia. This figure plots the time series of the percentage contribution of the total default risk premium to the 5-year CDS spread (in percentage) as described in section 7.1. The red area denotes the (27-68) Bayesian confidence intervals. The UK banks include: HSBC bank (HSBC), Barclays (BARC), the Royal Bank of Scotland (RBS), Santander UK (SUK), Lloyds Banking Group (LBG), Standard Chartered (STAN) and Nationwide (NW).

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