Are Bank Credit Risks Linked to Sovereign Credit Risks? Evidence from the Euro Area

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ABSTRACT

We study the link of sovereign and bank credit risks in the euro area by extracting default information from the most liquid 5Y CDS spreads over the period 2010-2014. Using German CDS spread and iTraxx financials index as proxies for systemic default risk of sovereigns and banks, we estimate the systemic credit risk and idiosyncratic credit risk of each sovereign and bank. We find that after controlling for both global macroeconomic shocks and country-specific risks, idiosyncratic sovereign credit risk change can explain bank credit risk change. We also find that co-integration between sovereign and bank only exists in Belgium and Greece. Results of error correction model reveal that credit risk of Belgian bank Granger-causes sovereign credit risk due to the massive government bail-out while in Greece this is not found since the crisis is rooted in the high fiscal deficit of Greek government.

JEL Classification: G12, G15, G21.

Keywords: CDS, credit risk, systemic risk, co-integration, Kalman filter

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1. INTRODUCTION

The European crisis seems to never stop. Several years after the 2008 global financial crisis, Europe is still plagued with doubts and fears of a systemic banking crisis. The Banking Union with its Single Supervisory and Single Resolution Mechanisms, barely established after months of negotiation, is just a step to better financial stability in the euro area. One regulation for the whole euro area seems to be a good thing, but one main problem remains: the economic situation significantly differs from one European country to another; the crisis is heterogeneous. Does the crisis come from government debts or does it come from banks? For example, the Greece case is primarily due to the deteriorating fiscal solvency of the government, while in Ireland the crisis comes from the distressed domestic banks. Yet, both types of crises happened in the euro area (Gennaioli et al. (2012)). In both cases, the relationship between government and banks appears obvious (Reinhart and Rogoff (2009)), but the strength of this relationship and its causality are not clear. For the European regulator, finding a solution requires an understanding of the genesis of the crisis.

In order to help find a solution to this problem, we analyze the connection between sovereign and bank credit risks in the euro area over the period of 2010 to 2014. First, we show that sovereign and bank credit risk is empirically related to each other. It is well known that sovereign and bank credit risk share huge commonality and are highly correlated. But it is not yet clear whether this correlation comes from the common risk exposures or the endogenous link between sovereign and its banks. A simple regression of bank CDS spreads on sovereign CDS spreads would yield a highly significant and economically large coefficient, but it is biased due to the common risks that affect both sovereign and bank. To address this issue, we implement a two-factor CDS pricing model to decompose the CDS spread into two parts: systemic component and idiosyncratic component. By removing the systemic component from the CDS spreads and controlling for other common risks, we are able to filter out the effect of systemic risks and identify the effect of idiosyncratic sovereign credit risk change on banks. In addition to the systemic risks, there could be country-specific economic shocks that affect both sovereign and bank. To control for this common impact, we follow Acharya et al (2014) and use bank equity returns as a proxy for domestic economic risk. The regression results show that a 10% increase in sovereign credit risk leads to about 1% in bank credit risk. Although the impact is economically small, it is always highly significant under different model specifications. Since it is hard to find an instrument to generate exogenous variations in idiosyncratic sovereign credit risk, we are not able to conclude any causality from the OLS regression between sovereign and bank, but at least we show that the correlation is not only due to the common macroeconomic exposures but also due to the link of implicit guarantee.

Next, we turn to co-integration analysis of sovereign and bank CDS spreads. Unable to conclude causality with OLS regressions, we implement a vector correction model to investigate if there exists any Granger causality between sovereign and bank. Since the implicit guarantee and potential bailout is aimed at systemically important banks, we select the most important bank in each country to analyze the co-integration instead of calculating the weighted average CDS spreads of all the banks. We use idiosyncratic default intensity estimated from the CDS spreads to eliminate the impact of systemic risks. We follow Engle-Granger procedure to test the co-integration relationship. The results show that only Belgium and Greece exhibit co-integration with their banks. Then we estimate an error correction model for Belgium and Greece and we find that lagged credit risks of Belgian bank Granger-cause sovereign credit risk while in Greece this is not found. The result is consistent with our expectation. The Belgian bank (KBC) was bailed out by the Belgian government during the financial crisis and the bail-out created a strong link between the bank and the government. For Greece, the crisis is rooted in the high fiscal deficit of the government but not domestic banking crisis, therefore we do not find any evidence that Greek bank risks Granger-cause sovereign credit risk. During this period, there are many countries in the euro area where there has been a domestic banking crisis, for example Spain and Ireland, but we do not find any co-integration for these countries empirically.

The paper proceeds as follows. In section 2, we give a short review of existing literature on the link between sovereign credit risk and financial sector fragility. In section 3, we describe the two-factor CDS pricing model introduced in Ang and Longstaff (2013) and show how to decompose the CDS spreads. Section 4 presents the data and descriptive statistics of sovereign and bank CDS spreads for each country. Section 5 is about the Kalman filter model estimation. In section 6, we present estimation results and comment on these results. Section 7 is the conclusion.

2. RELATED LITTERATURE

This paper is mainly related to two strands of the existing literature. First, the idea of this paper is inspired and supported by literature on the connection between sovereign credit risk and financial sector fragility. Second, this paper draws insights from the literature on CDS spreads dynamics during the financial crisis and sovereign debt crisis.

A. Sovereign Credit Risk and Financial Sector Fragility

As discussed in Gennaioli et al. (2012), there are two types of crisis evolution in the recent crisis in the euro area. The first type is that deteriorated public finances cause the fragility of domestic financial industry, as what happened in Greece. The second type is as in the Irish case where the government raises too much debt to bail out troubled domestic banks trapped in crisis and consequently accumulates high default risk of the sovereign bonds[2].

Most existing literature focuses on how the sovereign default affects the domestic financial sector. Borensztein and Panizza (2009) suggest that sovereign defaults lead to a loss of confidence in domestic financial system and poor balance sheets of banks, which largely restricts the lending capacities of banks. To investigate whether sovereign defaults give rise to banking crises, they construct a banking crisis index using 149 countries during the period 1975-2000. Their results show that the probability of having a banking crisis in year t conditional on a sovereign default in year t or t-1 is 11% higher than the unconditional probability and that the difference between conditional probability and unconditional probability is statistically significant. They also notice that this impact can work in the reverse way, i.e. the banking crisis leading to a sovereign default event due to the high fiscal costs involved. However, they find that the probability of sovereign bond default conditional on a banking crisis is only 2% higher than the unconditional probability. More importantly, this probability difference is not statistically significant. Although their findings indicate that the

[2] See Aizenman et al. (2013), Beirne and Fratzscher (2013) for an empirical discussion about the sovereign risk in the euro area.

sovereign default has a larger effect on the banking crisis than the other way around, we cannot easily conclude based on these historical observations of defaults and bank crises that the credit risk of financial sector does not affect the sovereign credit risk. The reason is that it is much harder to observe a sovereign credit event and thus the measure of conditional probability based on historical data could not fully reflect the true underlying connection between the credit risks of sovereigns and banks. It would be better to examine this relationship using some market indicator that continuously reflects the process of market expectation on sovereign credit risk.

To get more vigorous theoretical support, Bolton & Jeanne (2011), Acharya et al. (2014), and Gennaioli et al. (2013) model the link between sovereign credit risk and the financial sector fragility. Mayer (2012) constructs a model to explain how the sovereign credit risk and domestic financial system interact with each other. His model suggests that a large financial sector affects sovereign risk in two ways. On the one hand, it raises sovereign risk by increasing the potential losses in the event of a banking crisis. On the other hand, it lowers sovereign credit risk by committing the sovereign to servicing its debt in the future. Which effect dominates depends on variables such as size of the banking sector within the sovereign's economy, aggregate financial sector credit risk, and holdings of government bonds by domestic banks.

B. Studies of Sovereign and Bank CDS spreads

There is a growing literature on the relationship between sovereign and bank CDS spreads. Dieckmann and Plank (2011) document that domestic financial system of a country exhibits strong explanatory power for the behavior of sovereign CDS spread. First, they find that a country's pre-crisis exposure to the financial sector plays an important role in the sovereign credit risk during crisis. Controlling for a country's indebtedness (public debt over GDP ratio) and economic volatility, a country's pre-crisis exposure contributes to on average 40 bps of the sovereign CDS spread. They attribute this finding to the market expectation of potential financial sector bailouts and the consequent burdens for the government. Second, they show that a deteriorating financial sector gives rise to a larger CDS spread, especially for those countries with a dominating financial sector in their domestic economies.

Since the risk transfer can be two-way, deteriorating sovereign credit quality could also lead to an increasing risk of default of domestic financial institutions. That is to say, the CDS spreads of domestic financial institutions may depend not only on their own risks but also on the country's default risks. Acharya et al. (2014) study the sovereign and bank CDS spreads during the period of 2007 to 2011. They divide this period into three phases based on the announcements of bank bailouts. The first phase is prior to the burst out of financial crisis in September 2008. They observe during this period that bank CDS spreads rise dramatically while sovereign CDS spreads stay at low level. The second phase is the month of October 2008 when most Western European countries announced a bank support program including asset purchases, debt guarantees, equity injections, etc. They find that during this period bank CDS spreads dropped significantly while sovereign CDS spreads witnessed a notable increase. They explain this observation by the credit risk shift from the financial sector to the country. The third phase is the post-announcement period of bank bailouts. After the bank bailouts, bank and sovereign CDS spreads exhibit an evident co-movement due to some common risk factors. Although they recognize the potential two-way risk transfer, their empirical models focus on the impact of sovereign CDS spreads on bank CDS spreads. They use time fixed effects to control for global macroeconomic shocks and bank equity returns for country-specific shocks and show that sovereign credit risk positively affect bank credit risk.

3. CDS PRICING MODELS

To calibrate the CDS spreads observed in the market, we use a two-factor model proposed by Ang and Longstaff (2013). In their model, the default intensity is decomposed into two components: systemic default intensity and idiosyncratic default intensity.

The model allows two types of credit events to trigger default. The first type of credit event is idiosyncratic events, which are triggered by a specific sovereign or bank. The arrival of idiosyncratic events is modeled as the first jump of a Poisson process. The intensity of the Poisson process is a standard square-root process denoted by ξ_t. The dynamics of ξ_t is given by

$$d\xi_t = (a - b\xi_t)dt + c\sqrt{\xi_t}dW_t$$

The second type of credit event is triggered by systemic shock. We use different proxies for sovereign systemic shock and bank systemic stock. German CDS premium is used as a proxy for sovereign systemic risk in the euro area since Germany is considered as risk-free in the euro area and the change in German CDS premium essentially represents the systemic economic risk that affects all the countries in the euro area. In fact, Germany always has the lowest CDS spreads in the euro area and government bond yields of other euro area countries are quoted with respect to the yields of German sovereign bonds because German sovereign bonds are the risk-free benchmark, just like the treasury bonds in the United States. Besides, the German CDS premium has a strong correlation with the US CDS premium and US CDS premium has long been considered as a measure of global macro-economic risk, so we believe the default intensity implied in German CDS is a good proxy for the systemic credit risk of sovereigns in the euro area.

For bank systemic risk, we use iTraxx European Senior Financials index as a proxy. The index is composed of 25 major financial entities with investment grade credit ratings in Europe and represents the aggregate credit risk in the banking sector. Since the index is an arithmetic average of the CDS premiums of constituent banks, the idiosyncratic credit risk of each bank is expected to be diversified away in the index and only common systemic risk of the banking sector is captured by the index.

Unarguably, the financials CDS index will contain the sovereign systemic risk represented by the German CDS premium since both sovereigns and banks are exposed to the same macro-economic risks in the euro area. A two-factor model will not be able to distinguish the sovereign systemic risk and banking systemic risk in the bank CDS spreads. To further disentangle the two systemic risks, one would need a three-factor model. Since our aim is to study the relationship between the idiosyncratic risks of sovereigns and banks, it is not important to distinguish different sources of systemic risk and two-factor model is also easier to estimate.

The systemic shocks of sovereigns and banks are both modeled as arrival of a Poisson jump and the intensity of the Poisson process follows a standard square-root process denoted by λ_t. The dynamics of λ_t is given by

$$d\lambda_t = (\kappa - \mu\lambda_t)dt + \sigma\sqrt{\lambda_t}\,dW_t$$

To capture the heterogeneous fragility of sovereigns and banks in the event of a systemic shock, the default probability conditional on the systemic shock is modeled with a constant multiplier γ that is different for each sovereign and bank. γ can actually be viewed as systemic sensitivity of a sovereign or bank.

Under this model set-up, a CDS contract can be priced as

$$\begin{aligned}
s &= \frac{wE\left[\int_0^T D(t)(\gamma\lambda_t + \xi_t)\exp\left(-\int_0^t \gamma\lambda_s + \xi_s \ ds\right)dt\right]}{E\left[\int_0^T D(t)\exp\left(-\int_0^t \gamma\lambda_s + \xi_s \ ds\right)dt\right]} \\
&= \frac{wE\left[\int_0^T D(t)\gamma\lambda_t \exp\left(-\int_0^t \gamma\lambda_s + \xi_s \ ds\right)dt\right]}{E\left[\int_0^T D(t)\exp\left(-\int_0^t \gamma\lambda_s + \xi_s \ ds\right)dt\right]} + \frac{wE\left[\int_0^T D(t)\xi_t \exp\left(-\int_0^t \gamma\lambda_s + \xi_s \ ds\right)dt\right]}{E\left[\int_0^T D(t)\exp\left(-\int_0^t \gamma\lambda_s + \xi_s \ ds\right)dt\right]} \\
&= \frac{w\int_0^T D(t)A(\lambda,t)\mathrm{C}(\xi,t)dt}{\int_0^T D(t)A(\lambda,t)B(\xi,t)dt} + \frac{w\gamma\int_0^T D(t)B(\xi,t)F(\lambda,t)dt}{\int_0^T D(t)A(\lambda,t)B(\xi,t)dt} \\
&= s_{systemic} + s_{idiosyncratic}
\end{aligned}$$

where D(t) is the discount factor and A(), B(), C() and F() are functions that can be found in Ang and Longstaff (2013). Since the default intensity is additive in this model, we can easily decompose the CDS spread into systemic component and idiosyncratic component that are driven by systemic default intensity and idiosyncratic default intensity respectively. In the following empirical study, we will use the idiosyncratic components to analyze the relationship between sovereign and bank.

4. DATA DESCRIPTION

A. Countries

We use the CDS spreads of 10 countries in the euro area collected from Datastream, i.e. Germany, France, Italy, Spain, Portugal, Ireland, Greece, Belgium, Austria and Netherland. Among all the maturities, we choose the most liquid 5Y CDS contract written on senior debts. The variable to be estimated is the default intensity implied in the CDS spreads, so using the most liquid contract minimizes the noise of illiquidity and provides the most accurate information conveyed from the market. We ignore the term structure of CDS because CDS contracts with maturities other than 5Y are relatively rarely traded and the bid-ask quotes posted by the market makers are quite wide. Also what we are interested in is the relationship between the idiosyncratic default risks of sovereigns and banks but not the information content in the term structure, so we believe using 5Y contracts alone is sufficient for the purpose of this paper.

Considering that the daily change of CDS spreads is sometimes zero and daily data is very noisy, we use the weekly data of the CDS spreads as in most existing empirical literature.

The time period of the CDS data is from January 2010 to August 2014. We choose January 2010 as the beginning date because the European sovereign debt crisis broke out in 2010 when Greek debts became troublesome. Before 2010, the CDS spreads of European sovereigns and banks are mostly affected by the subprime crisis and the global economic downturn. We want to isolate this global impact and only focus on the local sovereign debt crisis in the euro area to examine the relationship between sovereign credit risk and bank credit risk. Another reason is that during and right after the financial crisis in 2008, the liquidity of CDS contracts decreased quickly and the bid-ask spreads were very large. Using CDS data in this period will have potential problems with liquidity premium that is found to be incorporated in the CDS premiums in many papers. It is necessary to mention that during our data period, there was a trading ban on naked sovereign CDS contracts. This ban does not seem to have a huge impact on the sovereign CDS liquidity since during the period around the announcement of ban, the bid-ask spreads do not experience a significant widening.

A total of 10 countries in the euro area are included, i.e. Germany, France, Italy, Spain, Portugal, Ireland, Greece, Belgium, Austria and Netherland.[3] Table 1 presents the summary statistics of the CDS spreads in every country.

[Insert Table 1 and Figure 1 Here]

Figure 1 plots the evolution of CDS spreads for the main countries in the euro area from January 2010 to August 2014. From the graph, we can see that before 2011, the sovereign

[3] Finland is not included because no Finnish banks have active CDS quotes in Datastream.

credit risks of most countries in the euro area are not prominent and their CDS spreads seem to move together all the time. During this period, Ireland and Greece have a relatively high level of CDS spreads due to the domestic banking crisis in Ireland and fiscal troubles in Greece. In November 2009, the new Greek government disclosed that the fiscal deficit was actually twice as large as previously believed. Following the disclosure, the Greek CDS started to explode in 2010.

On March 9th 2012, EMEA Credit Derivatives Determinations Committee of ISDA resolved that a restructuring credit event has occurred with respect to The Hellenic Republic (Greece). And this event accompanies the peak of sovereign credit crisis in the euro area. A few months after this event, the market calms down and the CDS spreads of most countries fall down rapidly and stay at relatively low level afterwards.

B. Banks

For each country in the euro area, we use one bank that is considered as the most important and influential. The selection criteria are as follows. First, we choose the bank with the largest asset in each country. Second, the bank must have liquid CDS contracts traded in the market and there is no missing data in Datastream during the selected time period. By applying these filters, we select the following banks as shown in Table 2. The size rank is the rank in the bank's home country for total assets at the end of fiscal year of 2009.

[Insert Table 2 here]

The time range of the banks CDS spreads is the same as that of sovereign CDS spreads, i.e. from January 2010 to August 2014. During this period, a 'Failure to Pay' credit event of Allied Irish Bank was determined by EMEA Credit Derivatives Determinations Committee of ISDA. Allied Irish Bank was recapitalized by the Irish government together with Bank of Ireland in February 2009. The financial link between Allied Irish Bank and Irish government and the huge idiosyncratic risk of the bank provides a good opportunity to study the interplay of credit risks between sovereigns and banks.

C. Risk-free Interest Rate

With regard to the risk-free interest rate in the pricing formula of CDS contract, we use the Euribor rate from one week to one year and Euribor interest rate swap from 2 year up to 5 year. Then we implement the standard cubic interpolation method to fill in the Euribor swap rate curve at the maturity of 1.5, 2.5, 3.5 and 4.5 year. With bootstrapping, the implied Euribor rate of maturities from 1.5 year up to 5 year can be calculated and the risk-free rate at any maturity can be interpolated from the Euribor rate curve from one week to 5 year.

The integrals in the CDS pricing formula involve the risk-free rate from t=0 to t=T. It would require interpolating the curve at lots of points when numerically evaluating the integral. To reduce the time cost in calculation, we use linearly interpolated interest rate. The consequence of this simplification is the pricing error of CDS contracts. As many people point out in the literature, the discount factor appears both in the protection leg and fixed leg, so the effect of interest rate choice is usually negligible and the pricing error is bound within the bid-ask spread of CDS contracts.

5. MODEL ESTIMATION

A. Kalman Filter

The CDS pricing model we use is based on mean-reverting square-root process. In addition to the three parameters in the square-root process, the latent initial values of the default intensity on each trading day also need to be estimated. Ang and Longstaff (2013) estimate the parameters by minimizing the sum of squared pricing errors. Since there are a considerable number of parameters to be estimated, it is quite challenging to find an efficient algorithm that is capable of searching global minimum in such a large parameter space.

In this paper, we use the extended Kalman filter to estimate the parameters of the default intensity process. To set up the Kalman filter, one needs to identify the associated transition equation and measurement equation. In the context of this paper, the transition equation describes how the default intensity is dynamically generated. For a state variable following square-root process, the discrete process can be written in AR(1) form

$$\lambda_t = \mu + \phi\lambda_{t-h} + v_t$$
$$where\ \mu = \theta(1-e^{-kh}), \phi = e^{-kh}$$

and v_t is normally distributed with zero mean and variance Q_t. Q_t can be found to be

$$Q_t = \frac{\sigma^2}{\kappa}[\lambda_{t-h}(e^{-kh} - e^{-2kh}) + \frac{\theta}{2}(1 - e^{-kh})^2]$$

The measurement equation is the CDS pricing function with input of default intensity process. The normal residual w_t captures the pricing error of a CDS contract. We assume the pricing error has a mean of zero and standard deviation of average bid-ask spread of CDS contracts of each name.

$$s_t = f(\lambda_t) + w_t$$

Since the CDS pricing function f is non-linear in the default intensity and the original Kalman filter is only able to estimate a linear measurement equation, we implement a first order Taylor's expansion at the one-step prediction of λ to linearize the measurement equation

$$\begin{aligned}
s_t &= f(\hat{\lambda}_{t|t-h}) + \left.\frac{\partial f}{\partial \lambda}\right|_{\lambda=\hat{\lambda}_{t|t-h}} \cdot (\lambda_t - \hat{\lambda}_{t|t-h}) + w_t \\
&= f(\hat{\lambda}_{t|t-h}) - \left.\frac{\partial f}{\partial \lambda}\right|_{\lambda=\hat{\lambda}_{t|t-h}} \cdot \hat{\lambda}_{t|t-h} + \left.\frac{\partial f}{\partial \lambda}\right|_{\lambda=\hat{\lambda}_{t|t-h}} \cdot \lambda_t \\
&= c + h\lambda_t + w_t
\end{aligned}$$

$$where\ \mathrm{c}= f(\hat{\lambda}_{t|t-h}) - \left.\frac{\partial f}{\partial \lambda}\right|_{\lambda=\hat{\lambda}_{t|t-h}} \cdot \hat{\lambda}_{t|t-h}, h = \left.\frac{\partial f}{\partial \lambda}\right|_{\lambda=\hat{\lambda}_{t|t-h}}$$

Next, we follow the procedures of Kalman filter to update the one-step prediction of default intensity and its variance with new information available at time t using linear projection.

$$\hat{\lambda}_{t|t} = \hat{\lambda}_{t|t-h} + \frac{hP_{t|t-h}(s_t - c - h\hat{\lambda}_{t|t-h})}{h^2 P_{t|t-h} + R}$$

$$P_{t|t} = P_{t|t-h}(1 - \frac{h^2 P_{t|t-h}}{h^2 P_{t|t-h} + R}) = \frac{RP_{t|t-h}^2}{h^2 P_{t|t-h} + R}$$

With the updated estimation of current default intensity, the default intensity at t+h can be estimated by

$$\hat{\lambda}_{t+h|t} = \mu + \phi\hat{\lambda}_{t|t}$$

$$P_{t+h|t} = \phi^2 P_{t|t} + Q$$

Since the residual wt in the measurement equation is assumed to be normally distributed, maximum likelihood estimation can be applied to estimate the unknown parameters that appear in the default intensity process. The probability density function is given by

$$f_{S_t|F_{t-1}}(s_t|F_{t-1}) = (2\pi)^{-0.5}(h^2 P_{t|t-h} + R)^{-0.5} \cdot \exp\left\{-\frac{1}{2}\frac{(s_t - c - h\hat{\lambda}_{t|t-h})^2}{(h^2 P_{t|t-h} + R)^2}\right\}$$

The log likelihood function is calculated as

$$\sum_{t=1}^{T} \log f_{S_t|F_{t-1}}(s_t|F_{t-1})$$

Through the recursion, the instantaneous default intensity at time t is estimated using information up to time t rather than the whole ex-post information set. To obtain the estimation of latent variables using all information available, backward deduction is applied to project the estimation on the whole information set. Starting from t=T-h, the default intensity at time T-h is estimated to be

$$\hat{\lambda}_{T-h|T} = \hat{\lambda}_{T-h|T-h} + \frac{P_{T-h|T-h}}{P_{T|T-h}}\phi(\hat{\lambda}_{T|T} - \hat{\lambda}_{T|T-h})$$

Then, all the previous default intensities can be calculated using the following equation.

$$\hat{\lambda}_{t|T} = \hat{\lambda}_{t|t} + \frac{P_{t|t}}{P_{t+h|t}}\phi(\hat{\lambda}_{t+h|T} - \hat{\lambda}_{t+h|t})$$

$$where\ J_t = \frac{P_{t|t}}{P_{t+h|t}} \cdot \phi$$

B. Procedures

First, we estimate the systemic intensity processes of sovereigns and banks. We use the extended Kalman filter to estimate the single-factor model on German CDS spreads and iTraxx financials index. Then we obtain the speed of reversion, long-run mean and volatility of the two processes and also the weekly default intensity filtered out by the Kalman filter.

In the second-stage estimation, with the estimated systemic intensity processes of sovereigns and banks in the first-stage estimation, we employ again extended Kalman filter to estimate the idiosyncratic intensity processes on each sovereign and bank one at a time. The separated identification of systemic component and idiosyncratic component makes it a lot easier to maximize the likelihood function although a joint estimation of systemic and idiosyncratic risks for all the entities could better extract and exploit the information from the data.

6. ESTIMATION RESULTS

A. Principal Component Analysis

To get a first look at the features of CDS spreads of sovereigns and banks in the euro area, we conduct principal component analysis for 9 sovereigns and 9 major banks in our sample. Greece and Irish banks are eliminated due to the occurrence of credit event and the suspended CDS trading after credit event. Table 3 presents the loadings of first two principal components and percentage of CDS spread variation explained by these two components.

[Insert Table 3 here]

The first principal component (PC1) can explain quite a large percentage of variation across the nine sovereigns, with the highest up to 96.08% for Portugal. This is not surprising given the evident co-movement of the sovereign CDS spreads in the euro area. On the contrary, the second principal component (PC2) seems to be incapable of capturing the remaining variation. This indicates that the idiosyncratic risk of each sovereign is quite different from each other and cannot be simply explained by one common factor.

The principal component analysis for banks reveals quite similar results. PC1 can explain about 70% to 98% of the variation of bank CDS spreads. And again, PC2 has very limited explanatory power for most of the banks except the Portugese bank.

These findings justify our choice of a two-factor model for the CDS spreads. The systemic factor in our model actually captures PC1 and the idiosyncratic factor captures the remaining idiosyncratic risk. Therefore, we expect the systemic sensitivity in our model to track the loading of PC1 in the principal component analysis and as we shall see in the section of systemic sensitivity, this is indeed the case.

B. Systemic Credit Risk

[Insert Figure 2 here]

Figure 2 plots the model-implied default intensity of German CDS spread. The systemic default intensity implied in the German CDS looks quite stationary overall. The peak over the whole period appears between September and December in 2011. During that time, Spain, Italy, Belgium, Ireland and Portugal are downgraded and the sovereign credit risk is rapidly spreading to the whole euro area. The mean-reversion speed of systemic credit risk seems to be very fast. The default intensity falls back to the normal level shortly after the peak and stays at very low level after 2013 when the situation is appeased.

C. Systemic sensitivity

Systemic sensitivity measures the augmented effect of systemic risk on a specific sovereign that is exposed to it. Therefore, the higher the systemic sensitivity is, the larger the credit exposure of an entity is to the systemic risk. The estimation results of systemic sensitivity for sovereigns and banks together with other parameters are presented in Table 4.

[Insert Table 4 here]

There are two countries that have a systemic sensitivity of less than one. They are Austria and Netherland, with systemic sensitivity equal to 0.76 and 0.38, respectively. If the credit risk of a country has a systemic sensitivity of less than one, it means that the credit risk of the country is not sensitive to the change of systemic credit risk. Actually it shares the same spirit as beta in the capital asset pricing model. For example, if the systemic credit risk is increased by 10%, the credit risk of a country with systemic sensitivity of 0.8 will only see an increase of 8% given the idiosyncratic credit risk unchanged. In fact, these two countries are indeed quite isolated from the systemic risk in the euro zone. The fiscal situations in these countries are stable and the economies are not as much integrated in the whole euro zone as other more important countries like Spain and Italy.

The three countries with the highest systemic sensitivities are Italy, Portugal and Greece. Greece has the highest systemic sensitivity and thus is most sensitive to the systemic credit risk. The magnitude of Greece's sensitivity is extremely large compared to the other countries. The reason might be that the default probability of Greece heavily weighs on Germany's standing and IMF's willingness to help. Portugal and Italy have also very high systemic sensitivity, meaning that the market considers them as highly sensitive to the systemic risk. Given the importance of these two countries in the euro area, this is not a surprising result.

Since the systemic sensitivity is in the same spirit as the loading on the first principal component, we expect the systemic sensitivity estimated from the no-arbitrage two-factor model to track the factor loading on PC1 in the principal component analysis. Figure 3 and Figure 4 plots the two parameters of sovereigns and banks respectively. From the graph, it is clear that these two parameters do follow the same track although they are not quantitatively equal. This is normal since the systemic sensitivity in the principal component analysis is a coefficient of a linear factor model while it appears in the power term in our two-factor model.

[Insert Figure 3, Figure 4 here]

D. Idiosyncratic Credit Risk

By observation, the idiosyncratic credit risk of sovereigns can be divided into two groups. Figure 5 plots the idiosyncratic credit risk of Netherland, Austria, and France. It is quite evident that Netherland and Finland share very similar pattern of idiosyncratic credit risk. They almost always move together and are very close to each other in magnitude. France starts with almost zero idiosyncratic credit risk since it is perceived to be as risk-free as Germany before the onset of crisis. After April/May 2010, the idiosyncratic credit risks of these four countries begin to move together. One possible explanation is that on 9th May 2010, the creation of European Financial Stability Facility (EFSF) binds together the credit risks of Eurozone countries by distributing the potential default loss to all the participating member countries. EFSF was jointly created by 16 member countries of the euro zone and is aimed to provide financial assistance to member countries that are unable to borrow from the market at acceptable rates. The capital guarantees are committed by all the participating eurozone countries based on the European Central Bank capital key weightings. Therefore, the introduction of EFSF is considered by the market as an integration of sovereign credit risk in the euro area and the CDS market seems to have well responded to this important event. The result that idiosyncratic sovereign credit risks co-move confirms the finding of Longstaff, Pan, Pedersen, and Singleton (2011) that sovereign credit risks share a large commonality across countries.

[Insert Figure 5 here]

The second group of countries includes Italy, Spain, Portugal, Ireland and Greece (PIIGS). Figure 6 presents the idiosyncratic default intensities of Italy, Spain, Portugal and Ireland. The default intensity of Greece is too high, so it is not plot in the figure. In 2010 and 2011, there is a significant increase of the idiosyncratic credit risks for all of the five countries. Then in 2012, Greece defaults on the sovereign debt and its idiosyncratic risk also reach the peak. However, for the other four countries, their idiosyncratic risks begin to decrease after July 2012 thanks to the central bank monetary policy and IMF aids. It is difficult to come to the conclusion that the default intensities of the four countries co-move during the whole period because apparently Ireland's default intensity sees a huge decline after July 2011 while the other countries are still suffering from soaring CDS spreads. What we can learn from the figure is that Italy and Spain share a lot of commonality and that Portugal and Ireland have co-movement before July 2011. It is not easy to explain the rationale behind this observation but this is how the market prices the credit risks of these countries.

[Insert Figure 6 here]

The idiosyncratic default intensities of banks exhibit a quite different pattern. Figure 7 plots the idiosyncratic default intensities of Deutsch Bank, BNP, ING, Unicredit, BBVA and ERSTE. These banks have almost constant idiosyncratic default intensity. The volatility of the idiosyncratic intensity process is only 1 to 2 percent and the change in credit risks of these banks is to a large extent driven by change in systemic banking risk. The fluctuations of their idiosyncratic risks are not priced into the CDS premium and the market treats them as almost constant.

[Insert Figure 7 here]

However, for the rest 3 banks, i.e. KBC, BCP and Alpha Bank, their idiosyncratic risks are not flat but change a lot over time, as shown in Figure 8. Greek bank have the largest volatility, followed by Portuguese bank and Belgium bank.

[Insert Figure 8 here]

E. Can sovereign credit risk explain bank credit risk?

As sovereign credit risk is highly correlated to bank credit risk, it is found in many literatures that sovereign credit risk is a determinant of bank credit risk and there exists co-integration between the two. We empirically investigate this relationship using the sovereign and bank CDS data in the euro area. Since sovereign and bank credit risk are both affected by global macroeconomic shocks and country-specific shocks, the challenge is to control these two common shocks to sovereign and bank so that the relationship between sovereign and bank credit risk is only driven by their guarantee link instead of common economic shocks.

Acharya et al. (2014) study the same question and they control for the global macroeconomic shocks with time fixed effects and a market-wide CDS index. First, we repeat their regression with only euro area countries to verify if the results are consistent. We estimate all regressions using weekly data. CDS data is quite noisy at daily level and can contain measurement errors that lead to bias in the estimate. Using weekly data smoothes out the measurement error and reduces stale observations. Specifically, the regression takes the form of

$$\Delta\log(BankCDS_{ijt}) = \alpha_i + \delta_t + \beta\Delta\log(SovereignCDS_{jt}) + \gamma_i\Delta Controls + \varepsilon_{ijt},$$

where the control variables are iTraxx Europe index and VDAX. iTraxx Europe index covers 125 of the most liquid CDS names in Europe with investment grade credit rating and is a good representative of market-wide credit risk. VDAX is the volatility index of options written on German DAX index and can reflect the overall risk attitude in the European market.

[Insert Table 5 Here]

The results of this regression are presented in Table 5. We try different specifications with or without bank fixed effects and we also allow for heterogeneity in the slopes of control variables. In all of the specifications, the coefficient of change in log sovereign CDS is always significant. When controlling for heterogeneity of slopes, the estimate is smaller but still statistically significant. Our estimates using weekly data are very close to those obtained by Acharya et al. (2014) even though they use daily data and include non-eurozone countries such as the United Kingdom and Scandinavian ones.

One major concern of this regression is that country-specific economic shocks are not well controlled and can cause endogeneity problems. The bank-fixed effect captures the time-invariant heterogeneity in banks and clearly does not capture country-specific shocks. Time fixed effects are the same to all the banks and sovereigns, thus they only capture the time varying global macroeconomic risks. To control for this country-specific factor, Acharya et al. (2014) propose to use bank equity returns as control variable because they argue that implicit government guarantee is aimed to protect bank debts but not equity. The stock price change should reflect the country-specific shocks and is arguably free of government impact.

Given this is true, there still leaves an omitted variable bias. Principal component analysis shows that bank CDS spreads in the eurozone share huge commonality and that PC1 explains 80-90% of bank CDS variations. Therefore, there is a banking industry factor that drives all the bank CDS spreads together. The same for sovereigns, there is a global macroeconomic factor that drives all the sovereign CDS spreads together. The omitted bank industry factor is correlated to the global macroeconomic factor contained in sovereign CDS spreads, and also to the other controls in the regression. To control for time varying banking industry effect and sovereign-specific shocks, we add iTraxx European Financial CDS index and equity returns to the regression model. The results are presented in Table 6.

[Insert Table 6 Here]

We find that adding financial CDS index will eliminate iTraxx Europe CDS index due to collinearity. This is not surprising because combining time fixed effects and financial CDS index will certainly capture most of the variation in the Europe CDS index. In column (1), (2) and (3), we find that the coefficients of log Sovereign CDS are significant and comparable to previous results. Column (4) controls for equity return and heterogeneity of slopes. The estimate is only significant at 90% confidence level and is economically smaller than all other estimates.

The regressions above all suffer from collinearity problems because the sovereign CDS change is highly correlated to any CDS index and VDAX. To better measure the credit risk link between sovereign and bank, we implement the two-factor model presented above to decompose CDS spread to two components: systemic component and idiosyncratic component. For sovereigns, the systemic exposure is measured based on German CDS spread; for banks, the systemic exposure is measured based on iTraxx European Financials index. German CDS spread is a proxy for the global macroeconomic risk contained in sovereign CDS spreads, while European Financials CDS index captures the credit risk in the whole European banking industry. Then we run regressions using the idiosyncratic components of sovereigns and banks. This approach is actually equivalent to controlling for sovereign-time effects for sovereigns and industry-time fixed effects for banks, but we avoid estimating high-dimensional fixed effects model. The model we estimate is as following

$$\Delta \log(BankCDS_{ijt}^{Idio}) = \alpha_i + \delta_t + \beta_1 \Delta \log(SovereignCDS_{jt}^{Idio}) + \beta_2 \Delta \log(SovereignCDS_{jt}^{Sys}) + \gamma_i \Delta Controls + \varepsilon_{ijt}$$

where the controls are equity return, iTraxx financials index and VDAX. Table 7 presents the estimation results.

[Insert Table 7 Here]

In all of the specifications, the coefficient on log change in idiosyncratic sovereign CDS spread is highly significant and economically larger than previous results. The column (4) finds that a 10% increase in idiosyncratic sovereign credit risk leads to about 1% increase in idiosyncratic bank credit risk. Using the idiosyncratic CDS spreads provides clearer identification of sovereign-bank relationship while using raw CDS spreads could not disentangle the effect of systemic risk change and idiosyncratic risk change.

F. Co-integration Analysis

Sovereign CDS spreads exhibit strong co-movement with bank CDS spreads in the recent euro sovereign debt crisis. To formally test whether there exists co-integration between sovereigns and banks, we use the idiosyncratic default intensities and adopt the standard

Granger-Engle procedure. The advantage of using idiosyncratic default intensities is that we are able to filter out the underlying systemic risks that both sovereigns and banks are exposed to and to only focus on the idiosyncratic part of the credit risks that arise from the economic and financial linkage between a sovereign and its bank. We do not use idiosyncratic CDS component for co-integration analysis because default intensities are more sensitive than CDS spreads and the dynamic relationship could be better identified using default intensity rather than CDS spreads.

The first exercise is to test if the idiosyncratic default process is stationary or not. We conduct the Dickey-Fuller test to find if there is a unit-root in the default process. Recall that in the CDS pricing model, the default intensity process is modeled as square-root process and the transition equation in the Kalman filter can be written as

$$\lambda_t = \mu + \phi\lambda_{t-h} + v_t$$
$$where\ \mu = \theta(1-e^{-kh}), \phi = e^{-kh}$$

If the mean-reverting speed is very close to zero or negative under the risk-neutral measure, the default intensity will exhibit non-stationary features.

Given the existence of a drift term in the default intensity process, we use the Dickey-Fuller test with drift to test the unit-root. The testing model with drift is

$$\lambda_t = \mu + \phi\lambda_{t-1} + \varepsilon_t$$

We find that the idiosyncratic intensity processes for the 9 countries in our sample all have unit-roots and thus are non-stationary.

Given that all the idiosyncratic default processes of countries and banks are non-stationary, our second exercise is to estimate the long-run equilibrium relationship. To empirically determine if there exists a linear relationship between the two processes, we estimate a linear model with intercept given below.

$$\lambda_t^{bank} = \alpha + \beta\lambda_t^{gov} + e_t$$

If indeed there is a long-term linear relationship, one should find the residual term to be stationary and the goodness-of-fit to be large enough. The estimation results of the linear model are presented in Table 8.

[Insert Table 8 Here]

Since it is impossible to directly test the unit-root on true residual terms from the long-term equilibrium model, we test on the estimated residuals from the OLS estimation. We regress the differenced residual on its first lag with different lag specifications. As the residuals are estimated from OLS model, there is no intercept or trend term.

$$\Delta \hat{e}_t = \rho \hat{e}_{t-1} + u_t$$

$$\Delta \hat{e}_t = \rho \hat{e}_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta \hat{e}_{t-i} + u_t$$

The null hypothesis is that the residuals are non-stationary, i.e. ρ=0. If the null cannot be rejected, then the residuals are non-stationary and the deviation from the long-term equilibrium is persistent. Hence, it cannot be concluded that there exists co-integration between the two variables. If the null is rejected, i.e. -2<ρ<0, then the residuals are stationary and there exists co-integration.

Since the estimated residuals are not the true ones generated from the long-term equilibrium model, the OLS estimation tends to minimize the residuals and therefore the estimated residuals from the long-term equilibrium model would actually be smaller than the true values. To correct for this bias, we use the critical values for the t-statistic of ρ proposed by Engle and Granger (1987). The estimation results of ρ are presented in Table 9.

[Insert Table 9 Here]

The results show that the null of no co-integration is rejected only for Greece and Belgium. This is not surprising since the R^2 of the long-run equilibrium regression is quite low for most countries except Portugal, Greece, Ireland and Belgium. When there is no good fit for the long-run relationship, the residuals are usually not stationary. In the case of Portugal and Ireland, the goodness of fit is quite high (49.5% and 76.5%), but the null of no co-integration is not rejected due to the non-stationary residuals. For Belgium, the co-integration is mainly due to the massive bailout programs during the post-crisis period in 2008. On 27 October 2008, the Belgian government agreed to strengthen KBC Bank NV/SA's capital by 3.5 billion euro. For this purpose, KBC issued on 19 December 2008 3.5 billion euro non-transferable, non-voting core capital securities to the Belgian state. Then on 22 January 2009, KBC reached an agreement with the Flemish Regional Government for a non-dilutive, core capital injection of 2 billion euro. Due to these capital injections from the Belgian government, the idiosyncratic credit risk of KBC is tightly linked to that of the government.

Therefore, for the following Granger-causality test, we will only include Greece and Belgium which are shown to have co-integration. With the estimated deviation from long-term equilibrium relationship, we estimate an error correction model composed of p lags of bank credit risk and q lags of sovereign credit risk. We set the lag parameters p and q to make the residuals exhibit no auto-correlation.

$$\hat{e}_{t-1} = \lambda_{t-1}^{bank} - \hat{\alpha} - \hat{\beta}\lambda_{t-1}^{gov}$$

$$\Delta\lambda_t^{gov} = c_1 + k_1\hat{e}_{t-1} + \sum_{i=1}^{p} a_{1i}\Delta\lambda_{t-i}^{gov} + \sum_{j=1}^{q} b_{1j}\Delta\lambda_{t-j}^{bank} + \varepsilon_{1t}$$

$$\Delta\lambda_t^{bank} = c_2 + k_2\hat{e}_{t-1} + \sum_{i=1}^{p} a_{2i}\Delta\lambda_{t-i}^{gov} + \sum_{j=1}^{q} b_{2j}\Delta\lambda_{t-j}^{bank} + \varepsilon_{2t}$$

k_1 and k_2 are the speed of adjustment parameters. They measure how fast the deviation from long-term equilibrium is restored. One of the two or both parameters are expected to be significantly different from zero. If neither parameter is significantly different from zero, it means there is no error correction and the system is reduced to a simple VAR system.

The advantage of error correction model is that one can analyze the Granger-causal effect between the variables. For example, if none of k_1 and a_{1j} (j=1,2,..p) is significantly different from zero, then it can be concluded that sovereign credit risk does not Granger-cause bank credit risk because all the lags of sovereign credit risk change do not explain the current bank credit risk change. For the same reason, if none of k_2 and b_{1j} (j=1,2,..q) is significantly different from zero, then bank credit risk does not Granger-cause sovereign credit risk.

In the empirical analysis, we use 1 lag and 3 lags for the error correction model of sovereign credit risk and bank credit risk. The estimation results are presented in Table 10 and Table 11.

[Insert Table 10, Table 11 Here]

In the case of Greece, the error correction term is always significant under both regressions. In the regression of sovereign risk, the error correction term is positive; while in the regression of bank risk, the error correction term is negative. This means that when the bank default intensity is higher than the sovereign default intensity, the former will decrease and the latter will increase, so the price discovery process is driven by both variables. Another finding is that none of the lagged changes in bank default intensity can explain the change in sovereign default intensity. This is consistent with the fact that in Greece the crisis is originated from the huge fiscal budget deficit, therefore the bank credit risk does not granger-cause the sovereign risk. At the same time, none of the lagged changes in sovereign default intensity can explain the change in bank default intensity. The channel of sovereign risk transfer is through the error correction term in the model.

For Belgium, we find that both error correction terms are significantly negative, but the term in the sovereign regression is smaller than that in the bank regression. This means that bank credit risk adjust more aggressively than sovereign credit risk when there is a deviation from the long-term equilibrium relationship. Moreover, the lagged changes in bank credit risk can explain the change in sovereign risk since the coefficient of the first lag of bank risk is always significant. Notably, this coefficient is negative because when the bank risk is decreased by the government bail-out programs, the sovereign risk will increase afterwards.

7. CONCLUSION

This paper identifies the source of credit risk change in the context of bank bail-outs and fiscal difficulty of the euro area countries. First, we document the correlation between sovereign and bank credit risk by looking at the idiosyncratic components in the CDS spreads. Controlling for both global macroeconomic shocks and country-specific risks, we find that 10% increase in sovereign credit risk lead to about 1% increase in bank credit risk. Then through the co-integration analysis, we find that in most countries there is no co-integration between sovereign and bank credit risks after controlling for systemic risks. Only two countries, Belgium and Greece, exhibit significant co-integration with their domestic banks. In the case of Belgium where banking crises obligated the sovereign to execute bail-out programs, the credit risk of bank granger-cause that of sovereigns due to the direct financial link created by the bail-out; while for Greece where the government has huge fiscal deficits due to aggressive fiscal policies, the credit risk of sovereigns is found to granger-cause that of banks due to the fact that domestic banks hold large amounts of sovereign debts of their home countries.

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Figure 1. Evolution of CDS spreads in the euro area

This figure plots the evolution of CDS spreads in the Euro Area for Germany, France Italy, Spain, Portugal and Ireland. Greece is not presented here because the Greek CDS spread goes too high compared to other countries and do not fit properly in the same figure. Netherland, Belgium and Austria are not presented here either due to their similarity to France. The CDS spread is measure in basis points. Source: Datastream

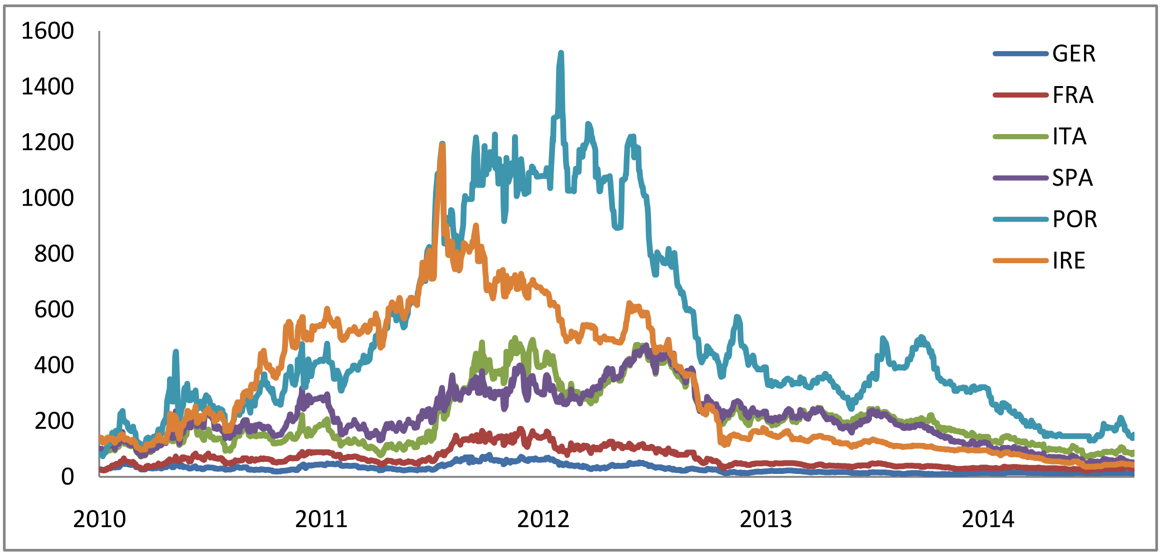

Figure 2. Systemic default intensity in the euro area

This figure plots the systemic default intensity estimated from weekly German CDS spread from January 2010 to August 2014 using a one-factor CDS pricing model.

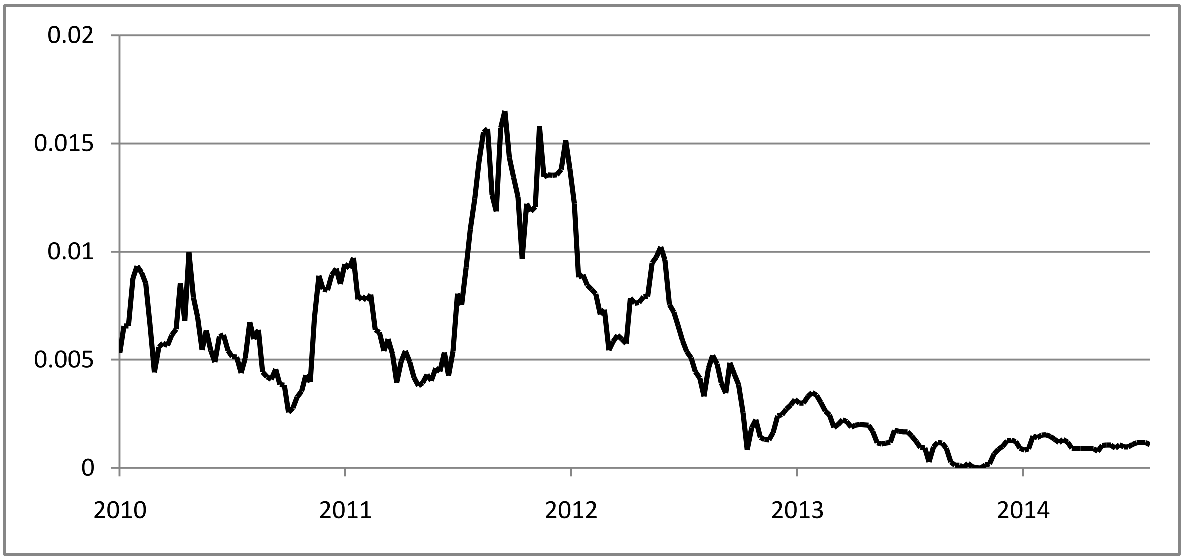

Figure 3. Factor loading of PC1 and systemic sensitivity of sovereign CDS spreads

This figure plots the factor loading of PC1 in sovereign CDS spreads and systemic sensitivity of each sovereign. The systemic sensitivity of Germany is normalized to 1.

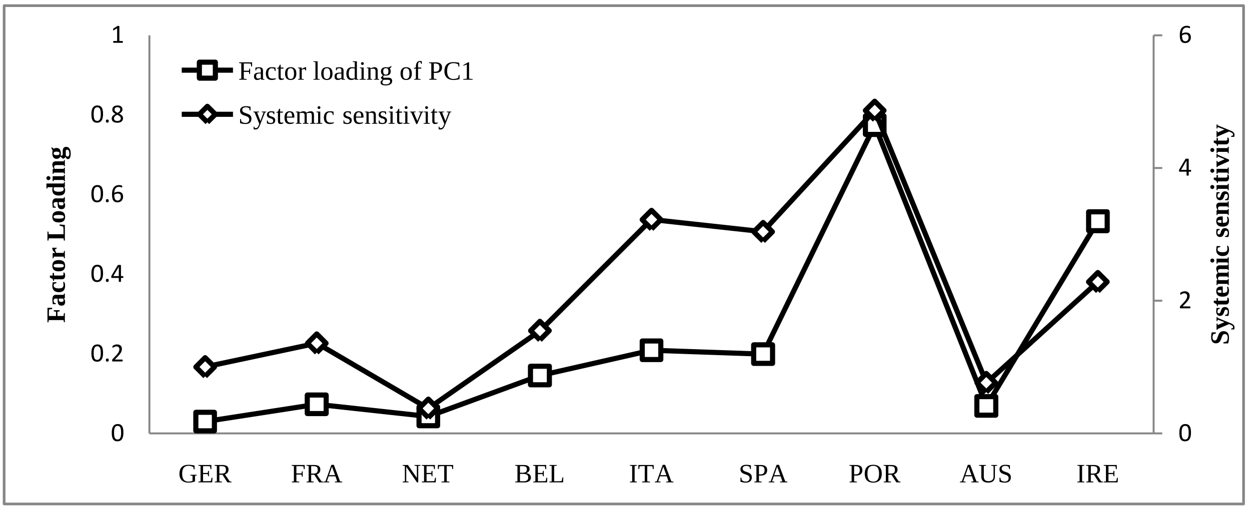

Figure 4. Factor loading of PC1 and systemic sensitivity of bank CDS spreads

This figure plots the factor loading of PC1 in bank CDS spreads and systemic sensitivity of each bank. The systemic sensitivity of the bank CDS index is normalized to 1.

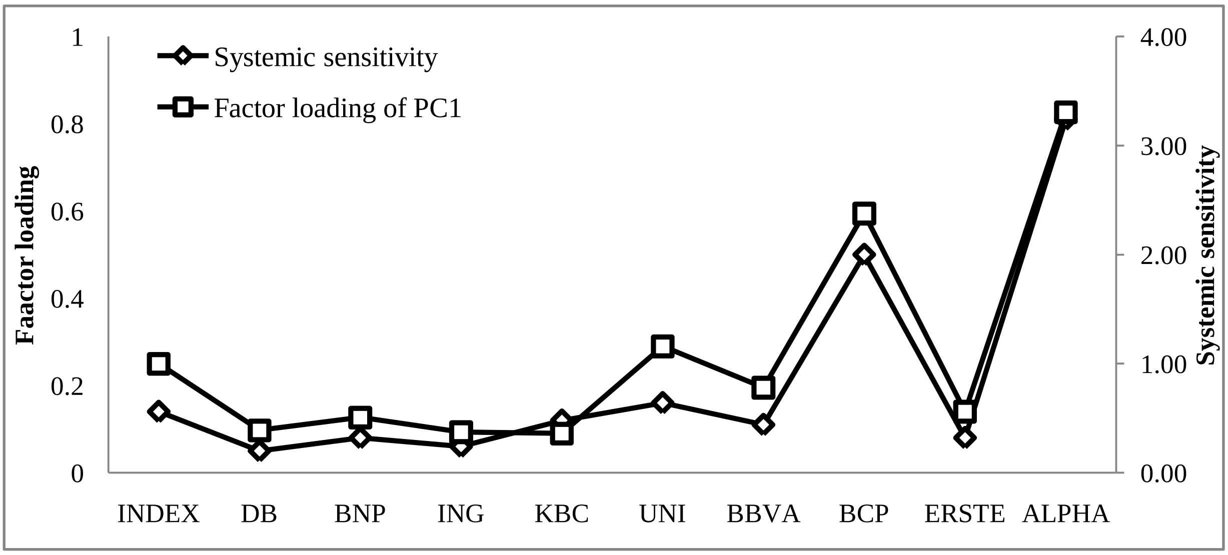

Figure 5. Idiosyncratic default intensity (France, Netherland, Belgium and Austria)

This figure plots the idiosyncratic default intensity estimated from a two-factor CDS pricing model for France, Netherland, Belgium and Austria. The data period is from January 2010 to August 2014 on a weekly frequency.

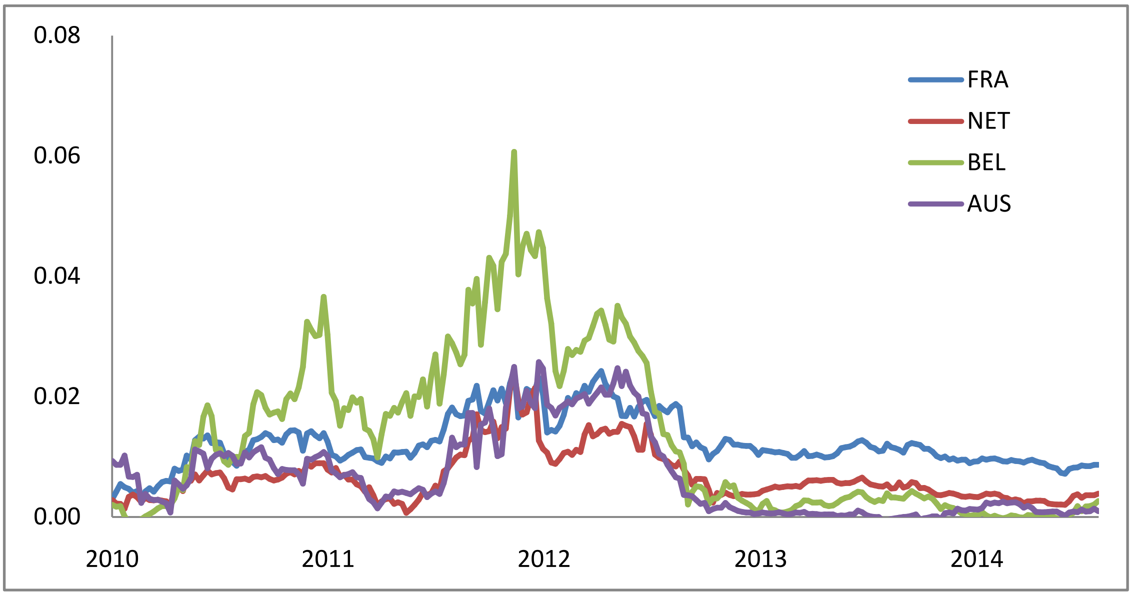

Figure 6. Idiosyncratic default intensity (Italy, Spain, Portugal and Ireland)

This figure plots the idiosyncratic default intensity estimated from a two-factor CDS pricing model for Italy, Spain, Portugal and Ireland. The data period is from January 2010 to August 2014 on a weekly frequency.

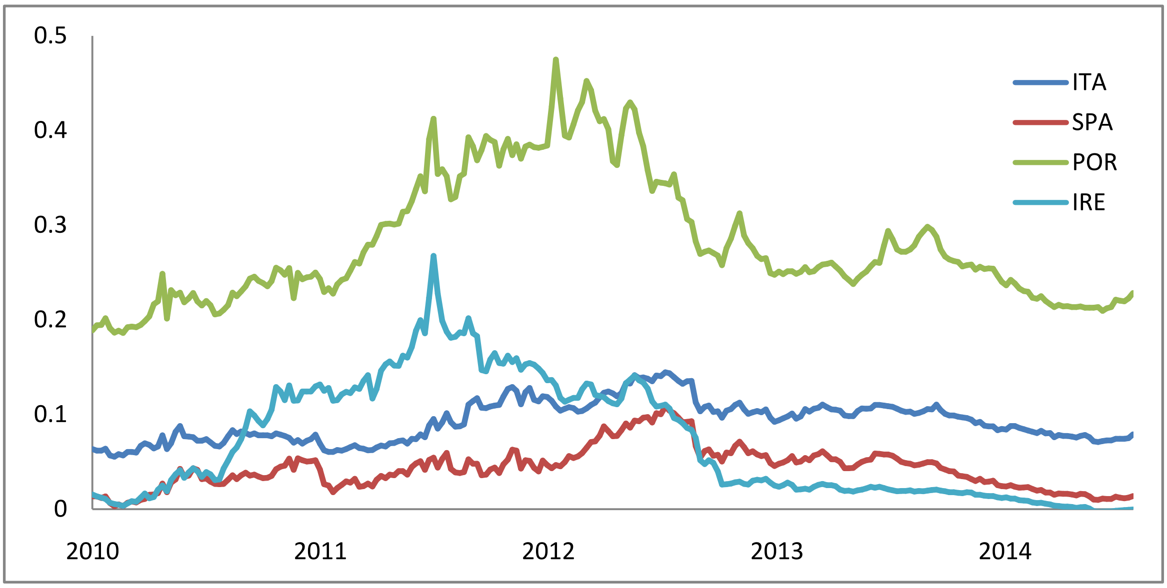

Figure 7. Idiosyncratic default intensity (Deutsche Bank, BNP Paribas, ING, UniCredit, ERSTE)

This figure plots the idiosyncratic default intensity estimated from a two-factor CDS pricing model for Deutsche Bank, BNP Paribas, ING, UniCredit, ERSTE. The data period is from January 2010 to August 2014 on a weekly frequency.

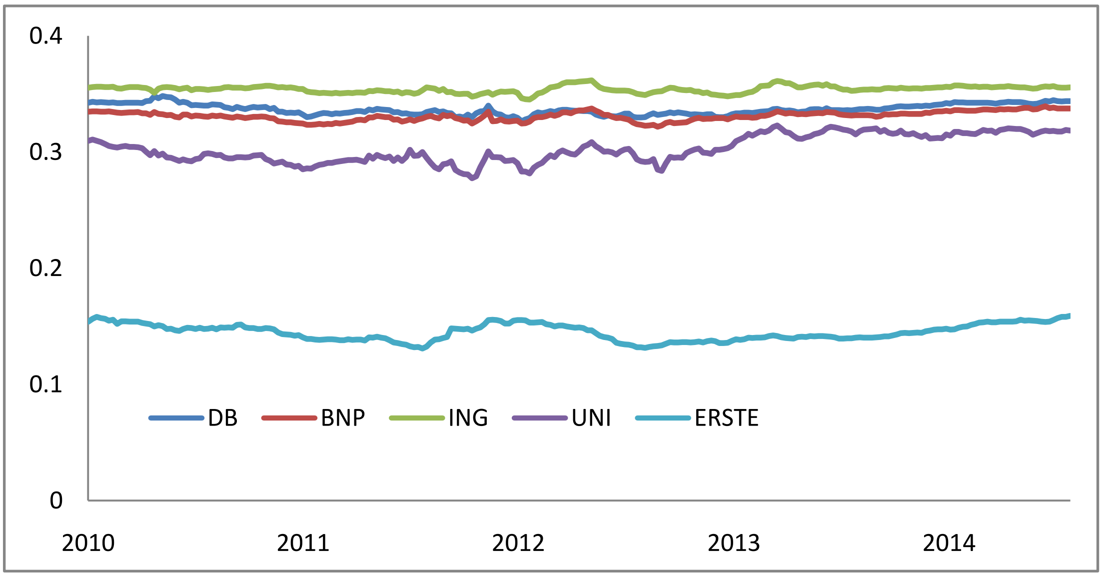

Figure 8. Idiosyncratic default intensity (KBC, Banco Comercial Português, Alpha Bank and Allied Irish Bank)

This figure plots the idiosyncratic default intensity estimated from a two-factor CDS pricing model for KBC, Banco Comercial Português, Alpha Bank and Allied Irish Bank. The data period is from January 2010 to August 2014 on a weekly frequency.

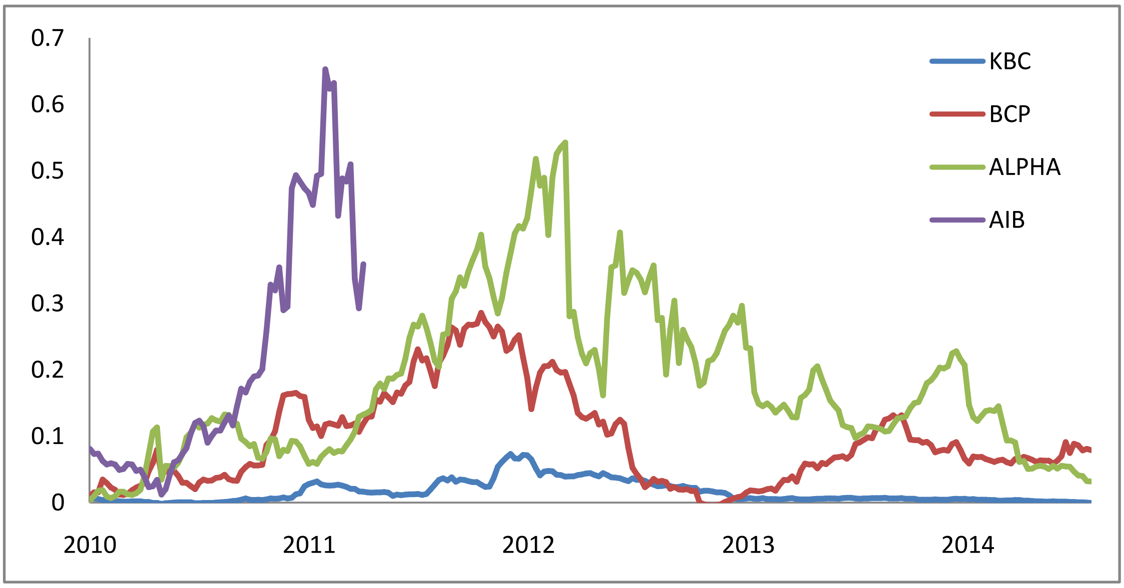

Table 1

Descriptive Statistics of Sovereign CDS Spreads

This table presents the descriptive statistics of weekly 5-year sovereign CDS spreads for the 10 countries in the euro area from January 2010 to August 2014. We report mean, median, standard deviation (Std Dev), minimum (Min), maximum (Max) and number of observations (N) for each country in the sample. Source: Datastream

	Mean	Median	Std Dev	Min	Max	N
GER	38.32	34.02	14.46	17.96	92.50	240
FRA	70.66	62.64	34.86	21.00	171.56	240
ITA	191.00	142.03	122.86	48.00	498.66	240
SPA	195.16	172.55	110.13	47.00	492.07	240
POR	456.54	299.31	408.30	37.00	1521.45	240
IRE	387.18	360.14	231.54	67.00	1191.16	240
GRE	1541.51	700.72	2475.26	66.50	14911.74	110
BEL	118.06	106.92	64.13	30.00	341.98	240
AUS	84.61	70.08	39.00	30.13	262.67	240
HOL	63.96	49.85	31.30	26.49	133.84	240

Table 2

Descriptive Statistics of Bank CDS Spreads

This table presents the descriptive statistics of weekly 5-year bank CDS spreads for the 10 banks in the euro area from January 2010 to August 2014. In each country, we select the bank with the largest total asset and most complete CDS trading quotes throughout the time period. We report bank's size rank in the domicile country, mean, median, standard deviation (Std Dev), minimum (Min), maximum (Max) and number of observations (N) for each bank in the sample. Source: Datastream

Country	Bank	Size Rank	Mean	Median	Std Dev	Min	Max	N
Germany	Deutschebank	1	282.02	264.01	108.42	107.66	552.18	240
France	BNP Paribas	1	120.34	104.39	41.23	58.52	308.14	240
Spain	BBVA	2	139.27	120.95	64.60	56.53	361.16	240
Portugal	Banco Comercial Português	2	133.99	121.33	51.99	50.60	269.57	240
Italy	Unicredit	1	197.91	160.14	96.74	84.01	498.35	240
Ireland	Allied Irish Bank	3	266.85	244.13	136.53	85.25	678.31	240
Greece	Alpha Bank	2	248.88	252.27	99.44	76.96	487.76	240
Belgium	KBC Bank	2	657.25	536.44	400.43	102.46	1772.50	240
Austria	Erste Group Bank AG	1	175.30	149.18	66.32	102.65	414.83	240
Netherland	ING	1	1191.54	972.50	618.75	358.96	2584.25	240

Table 3 OLS Regression of CDS Spreads on PC1 and PC2

This table presents the OLS regression of CDS spreads on PC1 and PC2 calculated from principal component analysis for the 9 countries and 9 banks in the euro area. We also run the regression for the bank CDS index that proxies for systemic banking risk. Greece and AIB are not included due to missing CDS data after credit event.

	PC1		PC2	
Country	β	R^2	β	R^2
GER	0.03	60.02%	-0.03	5.09%
FRA	0.07	81.90%	-0.01	-0.02%
NET	0.04	71.23%	0.02	0.93%
BEL	0.15	78.74%	-0.11	4.09%
ITA	0.21	67.23%	0.34	17.46%
SPA	0.20	70.34%	0.15	3.85%
POR	0.77	96.08%	0.44	2.99%
AUS	0.07	67.63%	-0.01	0.02%
IRE	0.53	81.78%	-0.81	17.99%
Bank	β	R^2	β	R^2
Bank CDS Index	0.14	93.11%	0.02	0.01%
DB	0.05	76.93%	0.00	-0.08%
BNP	0.08	88.39%	0.02	0.09%
ING	0.06	81.67%	0.01	0.04%
KBC	0.12	90.67%	-0.03	0.20%
UNI	0.16	79.13%	0.13	2.08%
BBVA	0.11	71.23%	0.11	2.75%
BCP	0.50	89.48%	-0.85	10.42%
ERSTE	0.08	79.80%	-0.03	0.42%
ALPHA	0.81	98.42%	0.49	1.36%

Table 4

Estimated Parameters of Two-factor Model

This table presents the estimated parameters of default intensities in a two-factor CDS pricing model. Germany and the CDS banking index have a normalized systemic sensitivity of 1.

Country	κ	μ	σ	Systemic Sensitivity	Bank	a	b	c	Systemic Sensitivity
GER	0.001	0.002	0.087	1	DB	-0.142	-0.048	0.013	0.39
FRA	-0.002	0.005	0.067	1.36	BNP	-0.142	-0.046	0.012	0.51
NET	0.000	0.004	0.089	0.38	ING	-0.149	-0.052	0.013	0.37
BEL	0.001	0.013	0.149	1.55	KBC	0.004	0.011	0.161	0.36
ITA	-0.024	0.007	0.106	3.22	UNI	-0.137	-0.042	0.030	1.16
SPA	-0.002	0.014	0.172	3.04	BBVA	-0.161	-0.061	0.024	0.78
POR	-0.003	0.169	0.359	4.86	BCP	-0.034	0.143	0.295	2.38
AUS	0.001	0.004	0.138	0.76	ERSTE	-0.059	-0.005	0.023	0.56
IRE	0.002	0.016	0.189	2.28	AIB	-0.029	0.110	0.558	1.91
GRE	-0.011	0.373	0.556	11.38	ALPHA	-0.012	0.214	0.427	3.31

Table 5

Bank and Sovereign Credit Risk (Using original CDS spreads)

This table presents the effect of change in sovereign CDS spread on change in bank CDS spread. The sample covers 9 sovereigns and 9 banks in the euro area from 2010 to 2014. ΔLog(BankCDS) is the weekly change in the natural logarithm of bank CDS. ΔLog(SovereignCDS) is the weekly logarithm change in the sovereign CDS of the country where the bank is headquartered. ΔLog(iTraxxEurope) is the change in the logarithm of iTraxx Europe index. The Δ(VDAX) is change in VDAX index. Column (3) and (4) include interactions between bank dummies and control variables to allow slope heterogeneity. All columns include week fixed effects. Column (2) and (4) include bank fixed effect. Standard errors are clustered at the bank level. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

	ΔLog(BankCDS)			
	(1)	(2)	(3)	(4)
ΔLog(SovereignCDS)	0.095***	0.093**	0.077**	0.075**
	(0.028)	(0.028)	(0.025)	(0.025)
ΔLog(iTraxxEurope)	-10.378***		-10.940***	
	(1.270)		(1.376)	
Δ(VDAX)	0.047***	0.012***	0.048***	0.010***
	(0.008)	(0.002)	(0.009)	(0.002)
Interactions between bank dummies and controls	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes
R^2	0.612	0.612	0.669	0.669
Observations	4886	4886	4886	4886

Table 6

Bank and Sovereign Credit Risk (Using original CDS spreads and controlling for equity return)

This table presents the effect of change in sovereign CDS spread on change in bank CDS spread by controlling for equity return. The sample covers 9 sovereigns and 9 banks in the euro area from 2010 to 2014. ΔLog(BankCDS) is the weekly change in the natural logarithm of bank CDS. ΔLog(SovereignCDS) is the weekly logarithm change in the sovereign CDS of the country where the bank is headquartered. ΔLog(iTraxxFinancials) is the change in the logarithm of iTraxx European Financials index. The Δ(VDAX) is change in VDAX index. Equity return is the bank's weekly equity logarithm return. Column (2) and (4) include interactions between bank dummies and control variables to allow slope heterogeneity. All columns include week fixed effects and bank fixed effect. Standard errors are clustered at the bank level. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

	ΔLog(BankCDS)			
	(1)	(2)	(3)	(4)
ΔLog(SovereignCDS)	0.093**	0.075**	0.087**	0.070*
	(0.028)	(0.025)	(0.029)	(0.025)
ΔLog(iTraxxFinancials)	0.419***	0.323***		
	(0.071)	(0.046)		
Δ(VDAX)	0.010*	0.010**	0.010***	0.008***
	(0.003)	(0.003)	(0.002)	(0.002)
Equity return			-0.076	-0.116***
			(0.046)	(0.024)
Constant	0.032*	0.025	0.041*	0.045*
	(0.013)	(0.013)	(0.018)	(0.017)
Interactions between bank dummies and controls	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R^2	0.612	0.681	0.614	0.684
Observations	4886	4886	4886	4886

Table 7

Bank and Sovereign Credit Risk (Using idiosyncratic CDS spreads)

This table presents the effect of change in idiosyncratic sovereign CDS on change in idiosyncratic bank CDS. The sample covers 9 sovereigns and 9 banks in the euro area from 2010 to 2014. ΔLog(BankCDS^{idio}) is the weekly change in the natural logarithm of idiosyncratic bank CDS. ΔLog(SovereignCDS^{idio}) is the weekly logarithm change in the idiosyncratic sovereign CDS of the country where the bank is headquartered. Equity return is the bank's weekly equity logarithm return. ΔLog(iTraxxFinancials) is the change in the logarithm of iTraxx European Financials index. The Δ(VDAX) is change in VDAX index. Column (3) and (4) include interactions between bank dummies and control variables. Column (2) and (4) include week fixed effects. All columns include bank fixed effect. Standard errors are clustered at the bank level. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

	ΔLog(BankCDS^{idio})			
	(1)	(2)	(3)	(4)
ΔLog(SovereignCDS^{idio})	0.129***	0.096***	0.126***	0.098***
	(0.027)	(0.024)	(0.027)	(0.024)
ΔLog(SovereignCDS^{sys})	0.113***	-0.193**	0.116***	-0.225***
	(0.017)	(0.053)	(0.019)	(0.045)
Equity return	-0.058**	-0.047*	-0.149***	-0.088**
	(0.018)	(0.022)	(0.009)	(0.025)
ΔLog(iTraxxFinancials)	-0.075**	-0.156***	-0.058***	-0.136**
	(0.021)	(0.038)	(0.011)	(0.037)
Δ(VDAX)	0.000	0.011*	-0.002***	0.011*
	(0.000)	(0.004)	(0.000)	(0.004)
Constant	0.002***	0.015	0.002***	0.018
	(0.000)	(0.011)	(0.000)	(0.010)
Interactions	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes
R^2	0.076	0.272	0.104	0.298
Observations	4886	4886	4886	4886

Table 8

Long-term Equilibrium Estimation

This table presents the OLS regression of bank's idiosyncratic default intensity on sovereign's idiosyncratic default intensity. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

$$\lambda_t^{bank} = \alpha + \beta \lambda_t^{gov} + e_t$$

	FRA	ITA	SPA	POR	IRE	GRE	BEL	AUS	HOL
α	0.33***	0.303***	0.373***	-0.117***	-0.018	0.046	0.002***	0.143***	0.354***
β	-0.28***	-0.004	0.001	0.754***	3.344***	0.148	0.975***	0.227***	-0.083***
Adj R^2	10.1%	-0.42%	-0.42%	49.5%	76.5%	84.7%	62.7%	4.54%	1.07%
N	239	239	239	239	66	110	239	239	239

Table 9

Co-integration Test

We test if there exists unit-root in the estimated residuals from the long-term equilibrium equation. We use an OLS regression with 0 to 4 lags to make sure that the result is robust. The t-statistics are compared with Engle-Granger critical values to determine significance of estimated coefficients. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

	FRA	ITA	SPA	POR	IRE	GRE	BEL	AUS	HOL
No lags									
rou	-0.083	-0.287	-0.041	-0.081	-0.150	**-0.306***	-0.053	-0.126	-0.042
Standard error	(0.030)	(0.153)	(0.019)	(0.028)	(0.066)	(0.074)	(0.021)	(0.054)	(0.022)
t-statistic	-2.81	-1.88	-2.24	-2.88	-2.28	-4.15	-2.54	-2.33	-1.92
1 lag									
rou	-0.091	-0.276	-0.039	-0.080	-0.132	**-0.268***	**-0.065***	-0.096	-0.059
Standard error	(0.051)	(0.155)	(0.019)	(0.038)	(0.044)	(0.080)	(0.021)	(0.034)	(0.021)
t-statistic	-1.81	-1.78	-2.09	-2.11	-2.03	-3.35	-3.21	-2.81	-2.77
2 lags									
rou	-0.092	-0.242	-0.041	-0.094	-0.140	**-0.343***	**-0.066**	-0.105	-0.056
Standard error	(0.052)	(0.158)	(0.019)	(0.039)	(0.046)	(0.082)	(0.021)	(0.039)	(0.022)
t-statistic	-1.79	-1.56	-2.14	-2.41	-2.06	-4.21	-3.05	-2.69	-2.54
3 lags									
rou	-0.104	-0.234	-0.044	-0.083	-0.174	**-0.328***	**-0.066**	-0.103	-0.064
Standard error	(0.073)	(0.109)	(0.019)	(0.030)	(0.469)	(0.090)	(0.022)	(0.036)	(0.022)
t-statistic	-1.45	-2.15	-2.30	-2.78	-2.71	-3.68	-3.04	-2.86	-2.86
4 lags									
rou	-0.095	-0.220	-0.046	-0.082	-0.195	**-0.314***	**-0.066**	-0.119	-0.066
Standard error	(0.058)	(0.164)	(0.019)	(0.031)	0.050	(0.096)	(0.022)	(0.047)	(0.023)
t-statistic	-1.65	-1.37	-2.36	-2.67	-2.31	-3.28	-2.97	-2.55	-2.85

Table 10

Error Correction Model for Sovereign Credit Risk

We estimate an error correction model with the estimated residuals from the long-term equilibrium equation. We use 1 lag and 3 lags to eliminate the auto-correlation in the residuals and conduct an F-test on the null that lagged bank credit risks do not Granger-cause sovereign credit risk. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

$$\Delta\lambda_t^{gov} = c_1 + k_1\hat{e}_{t-1} + \sum_{i=1}^{p} a_{1i}\Delta\lambda_{t-i}^{gov} + \sum_{j=1}^{q} b_{1j}\Delta\lambda_{t-j}^{bank} + \varepsilon_{1t}$$

	GRE	BEL
1 lag		
c1	0.036*	0.000
k1	**0.833****	**-0.060*****
a11	-0.293***	-0.124*
b11	0.339	**-0.164****
3 lags		
c1	0.032	0.000
k1	**1.170****	-0.0078***
a11	-0.157*	-0.171**
a12	0.221*	-0.194**
a13	-0.045	-0.010
b11	0.353	**-0.141***
b12	-0.995	0.069
b13	-0.255	-0.122

Table 11

Estimation Results of Error Correction Model for Bank Credit Risk

We estimate an error correction model with the estimated residuals from the long-term equilibrium equation. We use 1 lag and 3 lags to eliminate the auto-correlation in the residuals and conduct an F-test on the null that lagged sovereign credit risks do not Granger-cause sovereign credit risk. ***, ** and * indicates statistical significance at the 1%, 5% and 10% level respectively.

$$\Delta\lambda_t^{bank} = c_2 + k_2\hat{e}_{t-1} + \sum_{i=1}^{p} a_{2i}\Delta\lambda_{t-i}^{gov} + \sum_{j=1}^{q} b_{2j}\Delta\lambda_{t-j}^{bank} + \varepsilon_{2t}$$

	GRE	BEL
1 lag		
c2	0.004**	-0.000
k2	**-0.157***	**-0.084***
a21	-0.000	-0.090
b21	0.070	0.385***
3 lags		
c2	0.004*	-0.000
k2	**-0.129**	**-0.079***
a21	0.001	-0.091
a22	0.015	-0.001
a23	0.006	0.065
b21	0.046	0.397***
b22	0.290***	-0.031
b23	-0.294***	-0.049