Bank Credit Risk Networks: Evidence from the Eurozone Crisis

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Abstract

The European financial crisis has shown that the credit risk of large financial institutions is highly interconnected as a results of a number of linkages between entities like exposure to common assets and interbank lending. In this work we propose a novel methodology to study credit risk interdependence in large panels of financial institutions. We introduce a credit risk model in which bank defaults can be triggered both by systematic economy wide and idiosyncratic bank specific shocks. The idiosyncratic shocks are assumed to have a sparse conditional dependence structure that we call the bank credit risk network. An estimation strategy based on CDS data and Lasso-type regression allows to estimate the parameters of the model and to recover the bank credit risk network structure. We apply this technique to analyse the interdependence of large European financial institutions between 2006 and 2013. Results show that the credit risk network captures a substantial amount of dependence on top of what can be explained by systematic factors.

Keywords: Credit Risk, European Financial Crisis, Networks, CDS, Lasso

JEL: C33, C55, E44, F36, G12, G13, G15, G18

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1 Introduction

One of the lessons learnt from the recent financial crisis in Europe is the systemic relevance of the financial sector and the potential risks of interconnectedness. In Ireland and Spain, the surge in the default risk of individual banks jeopardized the entire financial sector and spilled over to the real economy. Moreover, cross-border linkages with banks in the Eurozone propagated the distress throughout Europe. In response to these events, current bank regulation focuses on regulating systemically relevant institutions. However, the detection of the network of credit risk interconnections between financial institutions and the identification of highly interconnected firms is still to this date an empirically challenging task.

The finance literature has identified two broad channels that induce dependence in the default risk of financial institutions: common exposure to a systematic shock and dependence between the idiosyncratic shocks of individual banks. As explained in Ang and Longstaff (2013), the systematic channel is associated with both macroeconomic or financial shocks. The effect of macroeconomic or financial shocks on the financial system has been the scope of extensive research, such as Calomiris and Mason (2003), Kritzman, Yuanzhen, Page, and Rigobon (2010) and Stein (2012). At the same time, dependence can arise among the idiosyncratic shocks to banks, both through direct and indirect connections. Direct counterparty exposures between banks stem from the interbank market or obligations such as syndication and have been studied in Allen and Gale (2000), Mistrulli (2011), Suhua, Yunhong, and Gaiyan (2013) or Hale, Kapan, and Minoiu (2013). Additionally, banks can be linked indirectly when holding similar portfolios, as shown in Gai, Haldane, and Kapadia (2011), and Caballero and Simsek (2013).

Ang and Longstaff (2013) develop a credit risk model that focuses on systematic shocks. The authors build upon the standard reduced form models for pricing credit derivatives used in the finance literature (e.g. Duffie and Singleton, 1999) and propose a multifactor affine model in which defaults of individual financial institutions can be triggered by either systematic or idiosyncratic shocks. Dependence across the idiosyncratic shocks of different institutions is however ruled out by assumption, and default dependence among financial institutions only arises because of the systematic channel.

Despite the relevance of the systematic channel, in a study of forty three financial crises Alfaro and Drehmann (2009) find that only half of them occurred before the macroeconomy experienced adverse economic shocks. This motivates us to extend the Ang and Longstaff (2013) modelling approach by allowing for network type dependence among the idiosyncratic shocks of individual banks. More specifically, we assume that the idiosyncratic shocks have a sparse conditional dependence network structure, which we call the Bank Credit Risk Network. The network is defined as undirected graph where vertices represent financial institutions and the presence of an edge between vertices i and j denotes that the financial institutions i and j are not independent conditionally on all other entities in the panel. We work under the assumption that the network is sparse, which in this work means that each financial institution is not connected with all other financial institution in the panel (i.e. the network is not complete). In our framework, the conditional independence network structure is entirely characterized by the inverse covariance matrix (also known as concentration matrix) of the idiosyncratic shocks. Exploiting well known results from the graphical literature (Dempster, 1972), we have that in our model i and j are conditionally independent iff the (i, j) entry of the inverse covariance matrix is zero. This allows us to obtain a sparse conditional dependence structure by constraining the concentration matrix of the idiosyncratic shocks to be sparse. Overall, in our model there are two channels that generate default dependence, the systematic channel and the idiosyncratic network channel. Our framework allows to study the map of interconnections among financial institutions after controlling for the influence of systematic shocks.

We derive closed form Credit Default Swap (CDS) pricing formulas as a function of the underlying parameters of the model. The CDS pricing formulas are then used to recover parameter values, including the Bank Credit Risk Network. Estimation is carried out by minimizing the squared discrepancy between observed CDS spreads and model implied CDS prices. The challenge of the estimation step consists of recovering the sparsity structure of the inverse covariance matrix of the idiosyncratic shocks. This hurdle is overtaken by applying LASSO type estimation (cf Peng, Wang, Zhou, and Zhu, 2009). The main feature of this approach is that it allows to simultaneously estimate the elements of the concentration matrix of the idiosyncratic shocks and select the non-zero entries.

We apply this methodology to a sample of top financial institutions from 10 selected euro zone countries in between 2006 and 2013. Our sample period includes two dramatic periods for banks and sovereigns in the euro zone. It spans both over the financial crisis of 2007/2008, which is widely referred to as the worst economic downturn since the Great Depression of the 1930s, and the sovereign debt crisis, through which several countries in Europe were faced with high government debt, soaring yield spreads on government bonds and bailout schemes to prevent financial institutions from collapsing. Our analysis brings forward a number of empirical insights, which are highly relevant both from a researcher and a policy maker perspective.

First of all, we document that standard models like Ang and Longstaff (2013) are not able to capture all cross sectional dependence across default intensities. Contrary to what is commonly assumed in the literature, we find significant dependence structures in the residuals even after conditioning on common factors. This has two crucial implications. Firstly, it implies that widely used standard approaches are not fully suitable to model structures which are given by CDS prices. While reduced form models often assume that co-movement in default risk can be fully explained by an appropriate number of factors, we show that this is indeed not the case and that we need to take into account direct idiosyncratic linkages between banks. This, in turn, implies that probability of default of a subset of entities can be severely underestimated when one does not take into account their position in the network. Since joint default probabilities are significantly affected by underlying structures, their omission can dangerous for risk assessment applications.

Second, find evidence of both intra- and inter-country linkages between banks in Europe. These links are obtained even after conditioning on the respective sovereigns, which capture systematic channels. For instance, we find that banks in Germany and France are particularly exposed to both Irish and Greek banks through the height of the sovereign debt crisis in Europe. This implies that idiosyncratic shocks affecting banks in those countries can quickly spread through the credit risk network and significantly harm banks headquartered in other European sovereigns, which in turn might face increased problems through guarantee schemes or effects on the real economy.

And third, we find that during crisis periods, heavily affected financial institutions become hubs in the center of the bank credit risk network, with both a high number and increased strength of connections. This is relevant from a contagion perspective, since otherwise healthy institutions in core countries can be affected by idiosyncratic shocks to troubled banks in the periphery. Contrary to factor approaches, our model allows to detect which institutions are central in the network and have high levels of interdependence. In crisis periods, these hub institutions can quickly spread adverse shocks and lead to major downturns, such that their identification and monitoring is crucial for the health of the financial system.

This research is related to a number of contributions in the literature. Firstly, our paper is related to the literature on network estimation techniques in the empirical finance literature. The list of contributions in this area is rapidly growing and it includes, among others, the work of Billio, Getmanksi, Lo, and Pellizzon (2012), Diebold and Yilmaz (2011), Hautsch, Schaumburg, and Schienle (2010), and Barigozzi and Brownlees (2013). Secondly, our work is related to the literature on pricing credit derivatives which includes, among others, the work of Duffie and Singleton (1999), Lando (1998) and Longstaff, Mithal, and Neis (2005).

The rest of the paper is structured as follows. Section 2 introduces the model and the estimation procedure. Section 3 described the sample of banks used for the analysis and Section 4 presents the main empirical findings of the paper. Concluding remarks follow in Section 5. Appendix A contains a detailed derivation of our model.

2 Model

We consider a panel of n financial entities labelled 1 to n. Credit events are modelled as jumps of a Poisson process with stochastic intensity. There are two different types of credit events which can trigger default.

The first type of event is a systematic shock, affecting simultaneously all entities in the economy. It is modelled as the jump of a Poisson process $M(t)$ with intensity parameter λ that follows a standard square root process,

$$d\lambda(t) = a(m - \lambda(t))dt + b\sqrt{\lambda(t)}dW(t)$$

where $W(t)$ denotes a Brownian motion. Conditional on a systematic shock, the probability that entity i defaults is denoted as γ_i,

$$\gamma_i = \text{Prob}(\text{default}_i | \text{ systematic default}) \ ,$$

The second type of event is an idiosyncratic shock that triggers default of the respective entity with certainty, modelled accordingly as the first jump of a Poisson process $N_i(t)$ with intensity parameter ξ_i that follows a standard square root process,

$$d\xi_i(t) = \alpha_i(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)}dB_i(t) \text{ with } i = 1, ..., n \ ,$$

where $B_i(t)$ denotes an entity specific Brownian motion independent of the one driving the systematic intensity process. We denote by $B(t)$ the vector of Brownian motions $(B_1(t), ..., B_n(t))'$, which is assumed to be correlated with covariance matrix Σt, that is

$$B(t) \sim \mathcal{N}(0, \Sigma t) \ ,$$

where Σ is assumed to be positive definite.

2.1 Credit Risk Network

In Ang and Longstaff (2013) it is assumed that the Brownian motions $B(t)$ driving the idiosyncratic shocks are independent. In this work we relax this and assume that the Brownian motion $B(t)$ has a covariance matrix Σ constrained to have a sparse inverse. That is, let K denote the inverse covariance matrix Σ^{-1} and let k_{ij} denote the (i, j) entry of K. Then, we assume that

$$|\{k_{ij} = 0, i \neq j\}| > 0 \ .$$

Thus, we constrain the concentration matrix of the Brownian motion $B(t)$ to be sparse.

First, we define the bank credit risk network among the banks in the panel based on conditional independence relations among the components. The network is defined as an undirected graph $\mathcal{N} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = 1, ..., n$ is the set of banks and $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$ is the set of edges. We then define two banks to be connected by an edge iff their idiosyncratic default shocks are dependent conditionally on the other shocks in the panel, that is

$$(i, j) \in \mathcal{E} \quad \Leftrightarrow \quad B_i(t) \not\perp B_j(t) \mid B_k(t) \quad \forall k \neq i, j.$$

It turns out that the Bank Credit Risk network can be equivalently characterized by the concentration matrix of the Brownian motion $B(t)$. Let the concentration matrix be denoted by K and its elements by k_{ij}. We can express the partial correlation between $B_i(t), B_j(t)$ as $\rho^{ij} = \frac{-k_{ij}}{\sqrt{k_{ii}k_{jj}}}$ where k_{ij} denotes the ij-th entry of K. It is well known that if we write $B_i(t)$ as

$$B_i(t) = \sum_{j \neq i} \beta_{ij} B_j(t) + u_i(t),$$

then $u_i(t)$ is independent of $B_j(t)$ for all $i \neq j$ if and only if

$$\beta_{ij} = \rho^{ij} \sqrt{\frac{k_{jj}}{k_{ii}}}.$$

Moreover, for such defined β_{ij},

$$u(t) \sim \mathcal{N}(0, Ut),$$

where U is the variance-covariance matrix with ij-th entry $\frac{k_{ij}}{k_{ii}k_{jj}}$.

2.2 Instantaneous probability of default

Combining both channels, for each entity the probability that it has not defaulted by time t equals the probability that no idiosyncratic shock occurs until time t times the probability that the entity does not default following any of potentially many systematic shocks (with probability $1-\gamma_i$ each), that is,

$$\begin{aligned}
&P\left(\text{no default}_i \text{ occurs by time t}\right) \\
&= P(N_i(t)=0)\sum_{j=0}^{\infty} P(M(t)=j)(1-\gamma_i)^j \\
&= \exp\left(-\int_0^t \xi_i(s)ds\right)\left[\sum_{j=0}^{\infty}\frac{1}{j!}\exp(-\int_0^t \lambda(s)ds)\left((1-\gamma_i)\int_0^t \lambda(s)ds\right)^j\right] \\
&= \exp\left(-\int_0^t (\gamma_i\lambda(s)+\xi_i(s))ds\right).
\end{aligned}$$

We can use the standard reduced form framework for valuing credit derivatives setting the instantaneous probability of default for entity i proportional to $\gamma_i\lambda(s)+\xi_i(s)$.

2.3 Determining the price of CDS spreads

Following Lando (1998), the value at time 0 of a claim with recovery fraction $(1-\omega)$ in case of default of the underlying, maturity T, and default intensity proportional to $\gamma_i\lambda(s)+\xi_i(s)$, is equal to

$$\begin{aligned}
CDS_i^{pro} &= \mathsf{E}^Q\left[\int_0^T \exp\left(-\int_0^t (r(s)+\gamma_i\lambda(s)+\xi_i(s))(1-\omega)ds\right)dt\right] \\
&= \mathsf{E}^Q\left[\omega\int_0^T D(t)(\gamma_i\lambda(s)+\xi_i(s))\exp\left(-\int_0^t(\gamma_i\lambda(s)+\xi_i(s))ds\right)dt\right]
\end{aligned}$$

where Q denotes the risk-neutral probability measure, and for all $t\in[0,T]$,

$$D(t)=\mathsf{E}^Q\left[\exp\left(-\int_0^t r(s)ds\right)\right]$$

is the value of a risk-less zero coupon bond with maturity T, where $(r(t), t \in [0, T])$ is the risk-less interest rate, which is assumed to be independent of all the intensity processes.

The premium leg of a CDS contract for entity i is equal to the discounted value of premium payments s_i in case there is no default.

$$\begin{aligned} CDS_i^{pre} &= \mathsf{E}^Q \left[s_i \int_0^T \exp\left(-\int_0^t (r(s) + \gamma_i \lambda(s) + \xi_i(s)) ds \right) dt \right] \\ &= \mathsf{E}^Q \left[s_i \int_0^T D(t) \exp\left(-\int_0^t (\gamma_i \lambda(s) + \xi_i(s)) ds \right) dt \right]. \end{aligned}$$

To meet the no arbitrage condition, the protection leg and the premium leg of a CDS contract must be equal and we can get out the value of premium payments,

$$s_i = \frac{\omega \mathsf{E}^Q \left[\int_0^T D(t)(\gamma_i \lambda(s) + \xi_i(s)) \exp\left(-\int_0^t (\gamma_i \lambda(s) + \xi_i(s)) ds \right) dt \right]}{\mathsf{E}^Q \left[\int_0^T D(t) \exp\left(-\int_0^t (\gamma_i \lambda(s) + \xi_i(s)) ds \right) dt \right]}. \tag{1}$$

As shown in the Appendix, we can rewrite the CDS spread for each entity i as

$$s_i = \frac{\omega \int_0^T D(t) \left(F^i(\lambda, t) H(\xi_i, t) + \gamma_i G(\xi_i, t) I^i(\lambda, t) \right) dt}{\int_0^T D(t) F^i(\lambda, t) G(\xi_i, t) dt}$$

where $\lambda := \lambda(0)$ and $\xi_i = \xi_i(0)$, and

$$\begin{aligned} F^i(\lambda, t) &= F_1(t) \exp(F_2(t)\lambda) \\ G(\xi_i, t) &= G_1(t) \exp(G_2(t)\xi_i) \\ H(\xi_i, t) &= (H_1(t) + H_2(t)\xi_i) \exp(G_2(t)\xi_i) \\ I^i(\lambda, t) &= (I_1(t) + I_2(t)\lambda) \exp(F_2(t)\lambda) \end{aligned}$$

with

$$
\begin{aligned}
F_1(t) &= \exp\left(\frac{-am(a-\psi_i)t}{b^2}\right)\left(\frac{\nu_i - 1}{\nu_i - e^{t\psi_i}}\right)^{\frac{2am}{b^2}} \\
F_2(t) &= \frac{a-\psi_i}{b^2} - \frac{2\psi_i e^{t\psi_i}}{b^2(\nu_i - e^{t\psi_i})} \\
G_1(t) &= \exp\left(\frac{-\alpha_i\mu_i(\alpha_i - \Phi_i)t}{\Gamma_i^2}\right)\left(\frac{\theta_i - 1}{\theta_i - e^{t\Phi_i}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}} \\
G_2(t) &= \frac{\alpha-\Phi_i}{\Gamma_i^2} - \frac{2\Phi_i e^{t\Phi_i}}{\Gamma_i^2(\theta_i - e^{t\Phi_i})} \\
H_1(t) &= \frac{\alpha_i\mu_i}{\Phi_i}(e^{\Phi_i t} - 1)\exp\left(\frac{-\alpha_i\mu_i(\alpha_i - \Phi_i)t}{\Gamma_i^2}\right)\left(\frac{\theta_i - 1}{\theta_i - e^{\Phi_i t}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}+1} \\
H_2(t) &= \exp\left(\frac{-\alpha_i\mu_i(\alpha_i - \Phi_i)t}{\Gamma_i^2} + \Phi_i t\right)\left(\frac{\theta_i - 1}{\theta_i - e^{\Phi_i t}}\right)^{\frac{2\alpha_i\mu_i}{\Gamma_i^2}+2} \\
I_1(t) &= \frac{am}{\psi_i}(e^{\psi_i t} - 1)\exp\left(\frac{-am(a-\psi_i)t}{b^2}\right)\left(\frac{\nu_i - 1}{\nu - e^{\psi_i t}}\right)^{\frac{2am}{b^2}+1} \\
I_2(t) &= \exp\left(\frac{-am(a-\psi_i)t}{b^2} + \psi_i t\right)\left(\frac{\nu_i - 1}{\nu_i - e^{\psi_i t}}\right)^{\frac{2am}{b^2}+2}
\end{aligned}
$$

and

$$
\begin{aligned}
\psi_i &= \sqrt{a^2 + 2\gamma_i b^2} \\
\nu_i &= \frac{a+\psi_i}{a-\psi_i} \\
\Phi_i &= \sqrt{\alpha_i^2 + 2\Gamma_i^2} \\
\theta_i &= \frac{\alpha_i + \Phi_i}{\alpha_i - \Phi_i} \\
\Gamma_i^2 &= \sum_{j\neq i, k\neq i} \beta_{ij}\beta_{ik}\sigma_{jk} + \frac{1}{k_{ii}}.
\end{aligned}
$$

2.4 Estimation

We are going to proceed as follows:

1. From the CDS prices, we will compute $\lambda := \lambda(0)$ and $\xi_i = \xi_i(0)$, for $i = 1, ..., n$.

2. From the CDS prices and the λ and ξ_i above, we will estimate the parameters a, m, b, α_i, and μ_i by minimizing the sum of squared deviations between the observed CDS prices and the true ones.

3. Finally, using the same minimizing procedure, we will estimate the partial correlations ρ^{ij}.

4. We will show consistency and sparsity when λ and ξ_i are the true default intensities.

3 Data Description

Our full sample period spans from January 1st, 2006 until December 31st, 2013. We divide the sample into four subperiods in order to capture different phases of the European crisis: The first period runs from January 1st, 2006 until August 1st, 2008 and is what we refer to the pre-crisis period preceeding the bankruptcy filing of Lehman Brothers on September 15th, 2008. We let the pre-crisis period end some weeks before the actual filing for Chapter 11 protection to avoid including a period of anticipation in the earliest subsample. The second period runs from August 1st, 2008 until April 1st, 2010 and is what we refer to as the financial crisis period. April 2010 is chosen as a breaking point, since it coincides with the official filing for financial help by Greece on April 23rd. We take this as a starting point for our third subsample, which we refer to as the sovereign debt crisis. This third period finishes on September 1st 2012, reflecting the initiation of the legal framework for Outright Monetary Transactions by the ECB to face the European debt crisis. Our fourth subsample accordingly runs from September 2012 until the end of our sample period on December 31st, 2013.

The data used in this study are daily mid-market spreads for one-year, two-year, three-year, five-year, seven-year and ten-year CDS contracts. We obtain quotes for a large sample of 71 banks headquartered in 10 selected European countries: Austria (AT), Belgium (BE), Germany (DE), Spain (ES), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL) and Portugal (PT) . A complete list of banks included in the sample can be found in Appendix B.

Additionally, we include spreads for sovereign CDS contracts of the same maturity for all 10 countries. The data used in this study are obtained from Markit, who collects CDS quotes from more than 30 market participants on a daily basis, and provides a composite spread only if on a given date observations from at least 2 different participants are available.

We make use CDS contracts for which the notional is denominated in Euro whenever available, and enhance our sample with notional denominated in US dollars otherwise. Since the CDS spreads themselves are denominated in basis points, we do not face the challenge of currency conversion.[1]

In order to calculate the values for zero-coupon bonds D(t) in the pricing formula, we refer to the Nelson-Siegel-Svensson curves estimated by Deutsche Bundesbank with daily frequency.

Tables 4 and 5 show descriptive statistics for sovereign and bank CDS in our sample, all spreads are denominated in basis points. We use 5-year CDS contracts for reporting descriptive statistics, since those are the ones most liquidly traded in the market. Comparing minimum and maximum values per country, we can see that spreads exhibit large time variation throughout the sample period, starting from values below or close to 5 basis points and increasing up to several hundred. For sovereign CDS, in all cases the mean is higher than the median, pointing towards right-skewed distributions with a large number of "negative" surprises.

Also in the cross-section, spreads exhibit considerable heterogeneity. For example, the

[1]Whenever both series are available, we can see that their correlation over time, both in levels and in first differences, is close to one.

German CDS spread never reaches values above 100 basis points, whereas Portuguese spreads increase to levels up to 17 times as high. In the case of Greece, CDS markets practically collapsed in a time window of several months surrounding the 52.3 % nominal haircut to government debt in March 2012, with spreads exceeding 10,000 basis points, i.e. the notional value of the underlying.

Compared with bank CDS spreads reported in table 5, with the exception of Greece, those exceed values of their respective sovereign. Cross-sectional variation in bank CDS spreads is lower than the one among sovereigns, while their variation over time is roughly comparable. The reason is simply that, while the macro-economic development through the crisis period affected perceived default intensities of both banks and sovereigns in a similar fashion, the heterogeneity in credit risk is much larger among different sovereigns in Europe than between different financial institutions.

4 Empirical Analysis

4.1 Systematic Factor and Systematic Exposures

4.1.1 Systematic default intensity

Figures 1 and 2 plot the risk-neutral default intensity process for all sovereigns in the sample, divided into core (Austria, Belgium, France, Germany, Netherlands) and periphery (Spain, Greece, Ireland, Italy, Portugal) countries. Through the height of the sovereign debt crisis, CDS markets for Greek sovereign debt stopped functioning with CDS spreads increasing up to more than 23,000 basis points (or 230 percentage points) for 5-year CDS contracts, such that we computationally obtain default intensities higher than 1 for the period from September 21, 2011 to June 6, 2013. For obtaining descriptive statistics, we exclude Greece from the analysis in this subperiod.

We can see that there is great commonality among the default intensities of the two subgroups: the average correlation amounts to 0.8793 among core countries, and to 0.8366 for periphery countries, respectively. At the same time, the average core and periphery spread are correlated only at 0.4273. We obtain the minimum default intensity for the Netherlands with 1.882 basis points, and the maximum default intensity smaller than 1 for Portugal with 29.98 percentage points. The mean default intensity for core countries amounts to 71 basis points with a standard deviation of 68 basis points, and to 424 basis points with a standard deviation of 531 basis points for periphery countries, respectively. With a constant lambda, these default intensities would translate to default probabilities of $1 - \exp(-0.0071) = 0.0071$ and $1 - \exp(-0.0424) = 0.0415$, respectively.

While being steadily close to zero at the beginning of our sample period, default intensities for core countries increase considerably following the bankruptcy of Lehman Brothers and a second time during the period we define as the sovereign debt crisis as shown in figure 1. Among core countries, the largest increase can be seen for Belgium with a default intensity of up to 582 basis points, accompanied by low economic growth rates, high unemployment and an unstable political situation at the peak of the sovereign debt crisis. Contrarily, Germany stays at the lowest level in our sample and never reaches an intensity higher than 1.53 percent.

The comparably low levels of default intensities for core countries even at crisis peaks sharply contrast the development for periphery countries depicted in figure 2. While showing only a slight increase in the aftermath of the bankruptcy of Lehman Brothers on September 15th, 2008, the sovereign default intensity for periphery countries increases considerably in the period from April 2010 to September 2012, which we refer to as the sovereign debt crisis. Comparing single country spreads, we can see that there is some heterogeneity in terms of the dates of national crises: while the intensity for the Irish sovereign reached its peak already on July 18th, 2011 and almost steadily declined after, the default intensities of all other periphery countries kept rising until fall of 2012, and only achieved substantial easing following the announcement of Outright Monetary Transactions by the ECB on September 6th.

4.1.2 Systematic sensitivity

We estimate bank-specific values of the systematic sensitivity parameter γ_i, that is, the conditional default probability of bank i given a shock to the national sovereign. Table 1 reports averages of the level and standard error of the conditional default probability of banks per country as well as the amount of variation in bank default intensity explained by the respective sovereign.

Table 1: Systematic Sensitivity

	Systematic Sensitivity	**Standard Error**	**Systematic Variation**
Austria	0.55519	0.033271	12.1448
Belgium	0.31553	0.037366	3.7728
Germany	0.27492	0.039125	2.8983
Spain	0.52198	0.030914	18.4206
France	0.46952	0.048175	6.2328
Greece	0.0014441	0.00091529	0.60685
Ireland	0.38751	0.38194	0.66106
Italy	0.65255	0.023993	31.3673
Netherlands	0.37053	0.076697	3.3236
Portugal	0.3832	0.019495	16.1886

Table 1: Country averages for the susceptibility parameter Gamma, its standard error and the time variation in bank default intensities explained by the respective default intensity of the sovereign.

4.1.3 Size of the systematic component

Following section 2.2, we can decompose the total default probability of bank i at time t into $\gamma_i\lambda(t)+\xi(t)$. Hence, we report the size of the systematic exposure for a given bank as the share of $\gamma_i\lambda$ in the total default intensity. The average value of the systematic exposure taken over all countries amount to 0.39, with the highest systematic exposure amounting to 1.0108 for Italian Banca Monte dei Paschi di Siena S.p.A, contrasting with an even slightly negative value for both Greek banks in our sample as well as Irish Nationwide Bank. We interpret negative values as a conditional default probability of zero, pointing towards a decoupling process of the banks' default probability from its respective sovereign.

Table 2: Average size of the systematic component per country

		Mean	Std. Dev.	Min.	Med.	Max.
Austria	**Pre-Crisis**	6.75	3.66	1.38	5.98	16.04
	Fin. Crisis	14.88	5.86	3.38	13.41	34.71
	Sov. Crisis	11.37	4.95	0.63	11.11	28.08
	Post Crisis	3.2	1.9	0.69	2.71	10.94
Belgium	**Pre-Crisis**	10.24	5.98	1.49	10.75	28.05
	Fin. Crisis	13.73	6.93	0.43	12.71	39.05
	Sov. Crisis	25.98	10.58	3.81	25.02	52.12
	Post Crisis	7.41	3.52	1.92	6.8	19.29
Germany	**Pre-Crisis**	3.42	2.21	0.44	3.44	9.3
	Fin. Crisis	4.29	2.48	0.86	3.59	13.75
	Sov. Crisis	3.06	1.78	0.24	2.72	9.69
	Post Crisis	2.48	1.73	0.47	1.98	10.36
Spain	**Pre-Crisis**	10.01	3.85	2.87	10.15	19.98
	Fin. Crisis	18.6	9.47	2.84	16.29	54.86
	Sov. Crisis	27.37	8.01	9.89	26.69	50.51
	Post Crisis	25.17	10.18	8.03	23.79	64.98
France	**Pre-Crisis**	9.14	5.72	1.42	9.22	25.38
	Fin. Crisis	10.28	6.91	1.88	8.31	37.59
	Sov. Crisis	14.74	6.57	1.27	14	38.49
	Post Crisis	9.11	4.19	1.68	8.81	25.8
Greece	**Pre-Crisis**	-0.03	0.02	-0.07	-0.02	0
	Fin. Crisis	-0.03	0.02	-0.1	-0.03	-0.01
	Sov. Crisis	-0.33	0.45	-1.67	-0.08	-0.04
	Post Crisis	-0.68	0.6	-1.66	-0.95	-0.01
Ireland	**Pre-Crisis**	5.56	2.95	0.66	5.92	11.18
	Fin. Crisis	14.99	5.48	0.4	14.67	30.94
	Sov. Crisis	16.02	7.83	4.68	13.6	38.95
	Post Crisis	1.23	0.66	0.4	1.13	5.49
Italy	**Pre-Crisis**	25.5	13.16	4.95	22.73	63.36
	Fin. Crisis	48.23	22.47	9.46	42.44	119.03
	Sov. Crisis	42.18	16.4	9.65	40.87	93.47
	Post Crisis	34.62	14.81	9.9	32.6	90.82
Ireland	**Pre-Crisis**	3.41	2.48	-1.1	3.81	9.15
	Fin. Crisis	5.46	3.53	-1.16	4.96	17.17
	Sov. Crisis	3.86	2.98	-2.56	3.66	12.67
	Post Crisis	3.39	2.06	-0.03	3.35	12.26
Portugal	**Pre-Crisis**	7.65	3.92	1.33	6.81	19.31
	Fin. Crisis	12.3	6.12	2.51	10.95	33.38
	Sov. Crisis	16.42	5.99	7.03	15.66	38.74
	Post Crisis	13.37	3.91	5.09	13.27	23.87

4.2 Idiosyncratic Factors and Credit Risk Networks

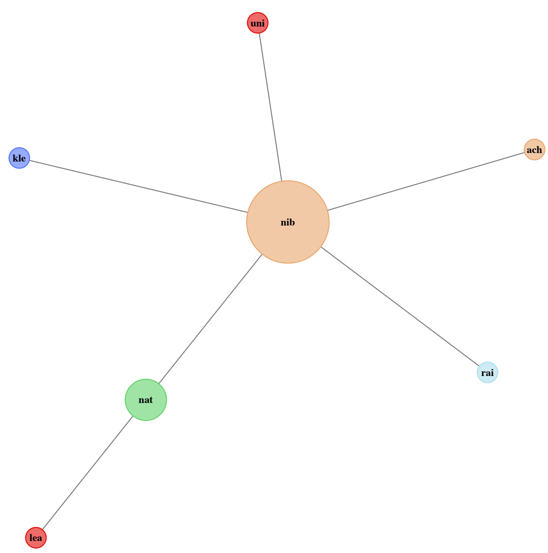
We show quartiles for idiosyncratic default intensities of banks grouped by country in figure 3.

4.3 The Bank Credit Risk Network

The following plots show the conditional dependence network structure obtained for our sample of banks from 10 European countries for the 4 subsample periods considered. The different colors of vertices mark the different countries of origins, whereas their size reflects the number of links to others. Vertices which have, conditional on all other entities, no links to any other vertex, are dropped from the plots.

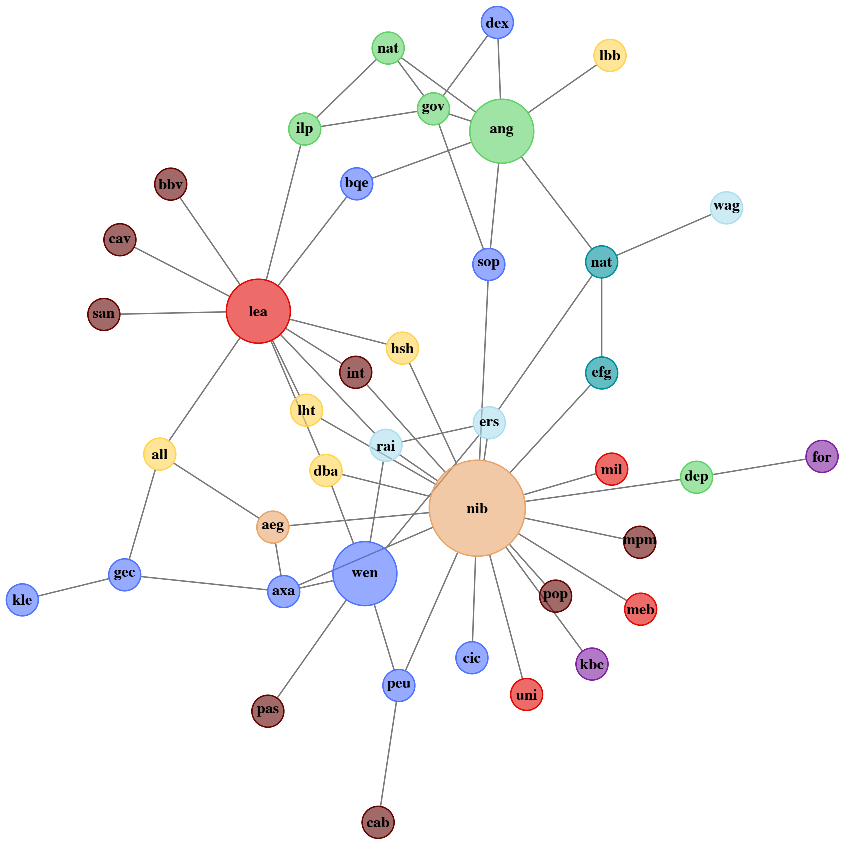
In general, we can see that the observed networks exhibit topological similarities to what has been shown e.g. for the interbank market or the credit default swap market: we can find clustering in terms of a core-periphery structure, where banks are not all connected to each other, but linked through a small number of banks constituting hubs in the center (see eg. Craig and von Peter (2010) or Peltonen, Scheicher, and Vuillemey (2013)). Furthermore, the Bank Credit Risk Network exhibits small world effects, meaning that the average path length between two vertices is short.

4.3.1 Period 1: Pre-Crisis



In the period preceeding the bankruptcy filing of Lehman Brothers, we can see that the conditional dependence network of bank credit risk is sparse. There is one main hub which connects a number of banks, but few cross-connections, and in total few banks linked through the network. The bank, which we found to be a hub, coincides with a bank facing early troubles through high exposures in the US subprime mortgage market: NIBC Bank NV, Netherlands. This coincides with the intuition, that correlations increase in crisis periods: banks, which were experiencing financial difficulties already in the years 2007 or early 2008 show up as more interconnected in our network.

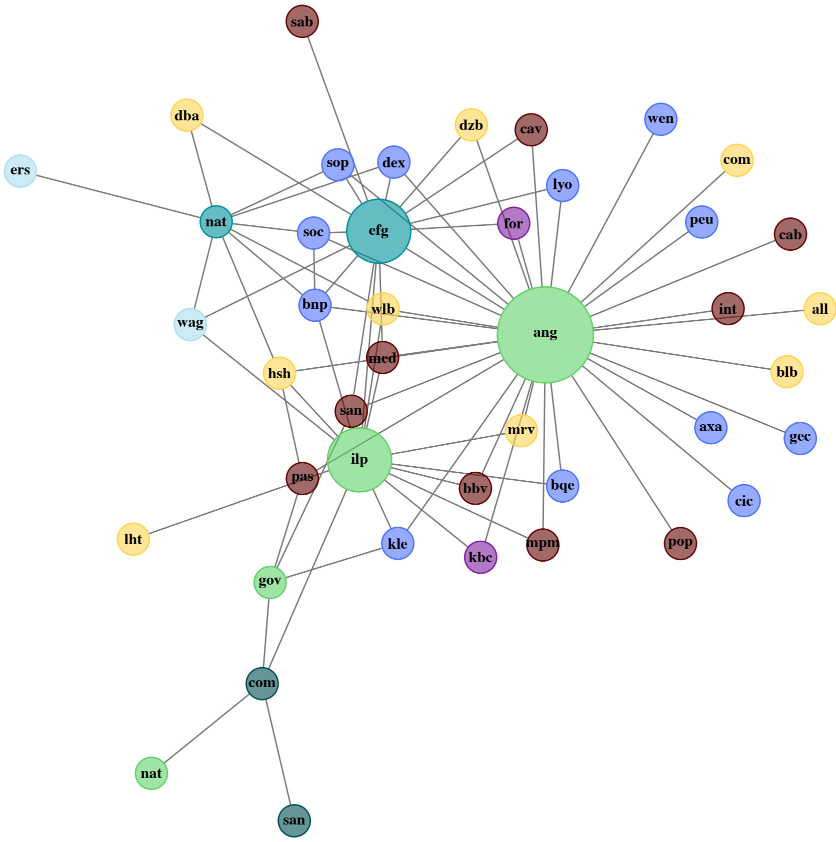
4.3.2 Period 2: Banking and Financial Crisis



In the period constituting the height of the banking and financial crisis, 2008 until 2010, we can see that the density of the network of credit risk interconnections increases dramatically. The hubs which we find in the bank credit risk network coincide with banks reporting larger losses during this period, in many cases due to high exposures to the real estate mortgage market, a segment which was facing high levels of distress throughout the financial crisis. Furthermore, the number of banks linked through the bank credit risk network increases drastically. Among the banks which are linked according to our model are 5 out of 7 German Landesbanken in our sample, as well as 9 out of 13 French and 7 out of 10 Spanish banks. In general, the banks which are less interconnected are the ones which either did not face major difficulties during the financial crisis or the ones which were nationalized by their respective sovereign. Also, contrary to what one might expect, larger banks do not show up as more interlinked in terms of credit risk. Both latter phenomena could reflect explicit guarantees or the expectation of implicit sovereign guarantees through a "too big to fail" argument: if investors expect, that an institution will not be allowed to fail, then its credit risk should also not or only to a small extent depend on other institutions. This is in line with Arora, Gandhi, and Longstaff (2012), who find that counterparty credit risk is not priced in the CDS for large financial firms.

The main channel which can explain the surge in interconnectedness during the financial crisis is exposure to common asset classes. Due to rapid price declines and the possibility of fire sales, banks' credit risk can be linked in case they hold similar portfolios as is shown e.g. in Caballero and Simsek (2013).

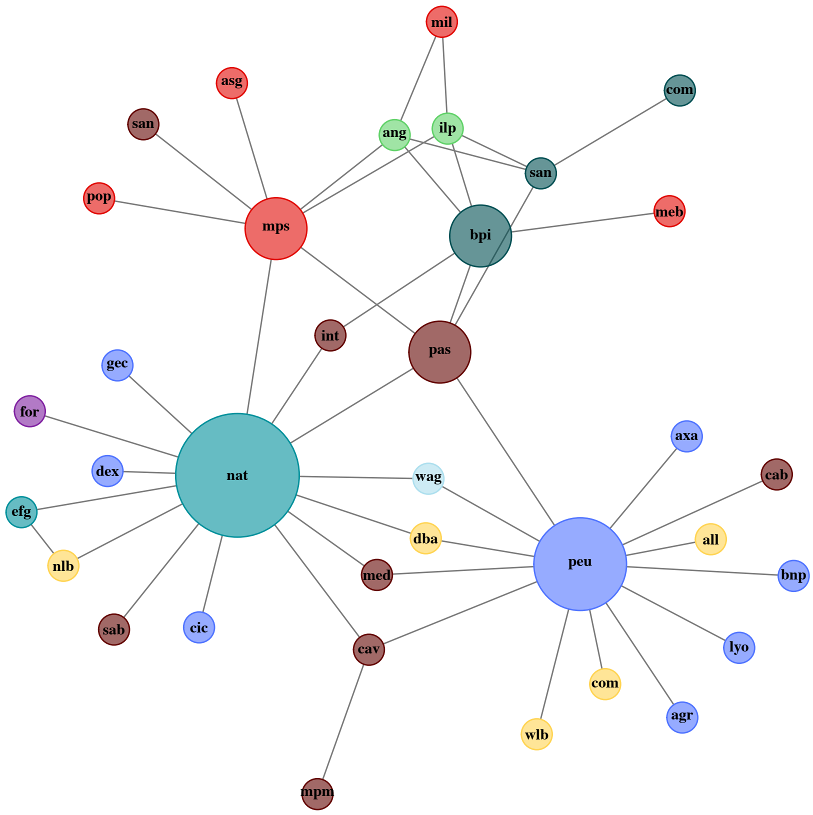
4.3.3 Period 3: Sovereign Debt Crisis



The entities constituting central hubs in the bank credit risk network shift from period 3 to period 4: whereas before mainly banks with heavy exposure to the subprime mortgage market appeared, now the focus lies on banks headquartered in GIIPS countries, which were facing troubles through the European sovereign debt crisis. The three banks constituting hubs in period 3 are one of the two Greek banks in our sample, EFG Ergasias, as well as two Irisk banks, Irish Life and Permanent and Anglo Irish Bank. Anglo Irish bank, which was nationalized in January of 2009, constitutes the main center and is linked to a large number of German, French and Spanish banks. It is the largest contributor of toxic assets to the Ireland's National Asset Management Agency and recorded the highest losses in Irish corporate history in two subseeding years in this period.

In general, we find evidence of large interconnectedness between banks from periphery countries on the one hand, and German and French banks on the other. This is highly relevant from a contagion perspective, since it implies that healthy banks in core countries could be quickly affected by idiosyncratic shocks to banks located in troubled European sovereigns.

4.3.4 Period 4: Post Crisis



In the fourth subperiod, we can see a surge in the interconnectedness of Portuguese banks, which is in line with the credit risk faced by the Portuguese sovereign at a comparably late stage: Portugal applied for a joint EU-IMF bailout package in May 2011. In line with the crisis in Ireland slowly becoming less severe, also Irish banks show up as less interconnected in the network. Next to National Bank of Greece, the bank constituting the second biggest hub is Banque PSA Finance which received a government bailout package in February 2013, in line with the observation that troubled banks constitute hubs in our network. In comparison to the pre-crisis plot, we can see that network structures significantly changed through the crises periods, and that interconnections between banks in the euro area have substantially increased through it.

5 Conclusion

References

Alfaro, R. and Drehmann, T. (2009). Macro stress tests and crises: what can we learn? Technical report, Bank for International Settlements.

Allen, F. and Gale, D. (2000). Bubbles and crises. Technical report, The Wharton School, University of Pennsylvania.

Ang, A. and Longstaff, F. (2013). Systemic Sovereign Credit Risk: Lessons from the U.S. and Europe. *Journal of Monetary Economics*, **60**, 493–510.

Arora, N., Gandhi, P., and Longstaff, F. (2012). Counterparty credit risk and the credit default swap market. *Journal of Financial Economics*, **103**.

Barigozzi, M. and Brownlees, C. (2013). NETS: Network Estimation for Time Series. Technical report, Barcelona GSE.

Billio, M., Getmanksi, M., Lo, A., and Pellizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, **104**, 535–559.

Caballero, R. and Simsek, A. (2013). Fire sales in a model of complexity. *Journal of Finance*, **68**, 2549–2587.

Calomiris, C. and Mason, J. (2003). Fundamentals, panics, and bank distress during the depression. Technical report.

Craig, B. and von Peter, G. (2010). Interbank tiering and money center banks. Technical report, Bank for International Settlements.

Dempster, A. (1972). Covariance Selection. *Biometrics*, (28), 157–175.

Diebold, F. X. and Yilmaz, K. (2011). On the network topology of variance decompositions measuring the connectedness of financial firms. Technical report, Federal Reserve Bank of Philadelphia.

Duffie, D. and Singleton, K. J. (1999). Modeling Term Structures of Defaultable Bond Yields. *Review of Financial Studies*, **12**, 687–720.

Gai, P., Haldane, A., and Kapadia, S. (2011). Complexity, concentration and contagion. *Journal of Monetary Economics*, **58**, 453–470.

Hale, G., Kapan, T., and Minoiu, C. (2013). Crisis transmission in the global banking network. Technical report.

Hautsch, N., Schaumburg, J., and Schienle, M. (2010). Quantifying time–varying marginal systemic risk contributions. Technical report.

Kritzman, M., Yuanzhen, L., Page, S., and Rigobon, R. (2010). Principal components as a measure of systemic risk. Technical report, MIT Sloan.

Lando, D. (1998). On cox processes and credit risky securities. *Review of Derivatives Research*.

Longstaff, F., Mithal, S., and Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? new evidence from the credit default swap market. *The Journal of Finance*.

Mistrulli, P. (2011). Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. *Journal of Banking and Finance*, **35**, 1114–1127.

Peltonen, T., Scheicher, M., and Vuillemey, G. (2013). The network structure of the cds market and its determinants. Technical report, European Central Bank.

Peng, J., Wang, P., Zhou, N., and Zhu, J. (2009). Partial correlation estimation by joint sparse regression models. *Journal of the American Statistical Association*, **104**, 735–746.

Stein, J. (2012). Monetary policy as financial stability regulation. *Quarterly Journal of Economics*.

Suhua, T., Yunhong, Y., and Gaiyan, Z. (2013). Bank capital, interbank contagion and bailout policy. *Journal of Banking and Finance*, **37**, 2765–2778.

A Proofs

Rearranging terms, the numerator of equation (1) can be expressed as

$$\omega \int_0^T D(t) \left(\mathsf{E}^Q \left[\exp\left(-\int_0^t \gamma_i \lambda(s) ds \right) \right] \mathsf{E}^Q \left[\xi_i(t) \exp\left(-\int_0^t \xi_i(s) ds \right) \right] \right.$$
$$\left. + \gamma_i \mathsf{E}^Q \left[\lambda(t) \exp\left(-\int_0^t \gamma_i \lambda(s) ds \right) \right] \mathsf{E}^Q \left[\exp\left(-\int_0^t \xi_i(s) ds \right) \right] \right) dt$$

A.1 Solving F

Set

$$F(\lambda, t) = F^i(\lambda, t) = \mathsf{E}^Q \left[\exp\left(-\int_0^t \gamma_i \lambda(s) ds \right) \right],$$

where $\lambda := \lambda(0)$. Applying Itô's formula to the discounted prices, which we also denote by $F(\lambda(t), t)$, we have that

$$dF = F_t dt + (a(m - \lambda(t))dt + \sqrt{\lambda(t)} dW(t)) F_\lambda + \frac{1}{2} b^2 \lambda(t) F_{\lambda\lambda} dt - \gamma_i \lambda(t) F dt$$

where

$$F_t = \frac{d}{dt} F(\lambda(t), t), F_\lambda = \frac{d}{d\lambda} F(\lambda(t), t), F_{\lambda\lambda} = \frac{d^2}{d\lambda^2} F(\lambda(t), t).$$

Since the discounted prices are martingales with respect to Q, we get that

$$\frac{b^2}{2} \lambda(t) F_{\lambda\lambda} + a(m - \lambda(t)) F_\lambda + F_t - \gamma_i \lambda(t) F = 0$$

subject to $F(\lambda, 0) = 1$.

In accordance with the CIR, we decompose

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

Then $F_1(t), F_2(t)$ need to fulfill the Riccati equations

$$\frac{b^2}{2} F_2(t)^2 - a F_2(t) - \gamma_i + F_2'(t) = 0$$

$$a m F_2(t) + \frac{F_1'(t)}{F_1(t)} = 0$$

subject to $F_1(0) = 1$ and $F_2(0) = 0$. The solution is given by

$$F_1(t) = \exp\left(\frac{-am(a-\psi_i)t}{b^2}\right)\left(\frac{\nu_i - 1}{\nu_i - e^{t\psi_i}}\right)^{\frac{2am}{b^2}}$$
$$F_2(t) = \frac{a-\psi_i}{b^2} - \frac{2\psi_i e^{t\psi_i}}{b^2(\nu_i - e^{t\psi_i})}$$

where

$$\psi_i = \sqrt{a^2 + 2\gamma_i b^2}$$
$$\nu_i = \frac{a+\psi_i}{a-\psi_i}.$$

A.2 Solving I

Set

$$I(\lambda, t) = I^i(\lambda, t) = \mathsf{E}^Q\left[\lambda(t)\exp\left(-\int_0^t \gamma_i\lambda(s)ds\right)\right].$$

Applying Itô's formula to the discounted prices also denoted by $I(\lambda(t), t)$, we get that

$$dI = I_t dt + (a(m - \lambda(t))dt + b\sqrt{\lambda(t)}dW(t))I_\lambda + \frac{1}{2}b^2\lambda(t)I_{\lambda\lambda}dt - \gamma_i\lambda I dt.$$

Under Q, the discounted prices are martingales, so we get

$$\frac{b^2}{2}\lambda(t)I_{\lambda\lambda} + a(m - \lambda(t))I_\lambda + I_t - \gamma_i\lambda(t)I = 0$$

subject to the boundary condition $I(\lambda, 0) = \lambda$.

Again, we decompose

$$I(\lambda, t) = (I_1(t) + I_2(t)\lambda)\exp(F_2(t)\lambda).$$

Then, we obtain the Riccati equations

$$(am + b^2)F_2(t) - a + \frac{I_2'(t)}{I_2(t)} = 0$$
$$amI_2(t) + amI_1(t)F_2(t) + I_1'(t) = 0.$$

Substituting $F_2(t)$ and solving the equations using the initial conditions $I_1(0) = 0$ and $I_2(0) = 1$, we get that the solution is given by

$$I_1(t) = \frac{am}{\psi_i}(e^{\psi_i t} - 1)\exp\left(\frac{-am(a-\psi_i)t}{b^2}\right)\left(\frac{\nu_i - 1}{\nu - e^{\psi_i t}}\right)^{\frac{2am}{b^2}+1}$$
$$I_2(t) = \exp\left(\frac{-am(a-\psi_i)t}{b^2} + \psi_i t\right)\left(\frac{\nu_i - 1}{\nu_i - e^{\psi_i t}}\right)^{\frac{2am}{b^2}+2}.$$

A.3 Solving G

Recall that for each $i = 1, ..., n$

$$G(\xi_i, t) = \mathsf{E}^Q \left[\exp\left(-\int_0^t \xi_i(s) ds \right) \right],$$

where $\xi_i := \xi_i(0)$. Applying Itô's formula, we get that

$$dG = G_t dt + G_{\xi_i} d\xi_i + \frac{1}{2} G_{\xi_i \xi_i} < d\xi_i, d\xi_i > .$$

Therefore, the discounted prices satisfy

$$dG = G_t dt + (\alpha_i(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)} dB_i(t)) G_{\xi_i} + \frac{\Gamma_i^2}{2} \xi_i(t) G_{\xi_i \xi_i} dt - \xi_i(t) G dt$$

where

$$\Gamma_i^2 = \sum_{j \neq i, k \neq i} \beta^{ij} \beta^{ik} \sigma_{jk} + \frac{1}{k_{ii}}.$$

Under Q, discounted prices $G(\xi_i(t), t)$ are martingales, so it holds that

$$\frac{\Gamma_i^2}{2} \xi_i(t) G_{\xi_i \xi_i} + \alpha_i(\mu_i - \xi_i(t)) G_{\xi_i} + G_t - \xi_i(t) G = 0$$

subject to the boundary condition $G(\xi_i, 0) = 1$.

Again, we decompose

$$G(\xi_i, t) = G_1(t) \exp(G_2(t) \xi_i).$$

Then, for the partial differential equation to be satisfied, $G_1(t)$, $G_2(t)$ need to fulfill the Riccati equations

$$\frac{\Gamma_i^2}{2} G_2^2(t) - \alpha_i G_2(t) + G_2'(t) - 1 = 0$$
$$\alpha_i \mu_i G_2(t) + \frac{G_1'(t)}{G_1(t)} = 0$$

subject to the initial conditions $G_1(0) = 1$ and $G_2(0) = 0$. Observe that these are the same equations than for $F_1(t)$ and $F_2(t)$ with $\Gamma_i = b$, $\alpha_i = a$, $\mu_i = m$ and $\gamma_i = 1$. Hence, the solution is

$$G_1(t) = \exp\left(\frac{-\alpha_i \mu_i (\alpha_i - \Phi_i) t}{\Gamma_i^2} \right) \left(\frac{\theta_i - 1}{\theta_i - e^{t\Phi_i}} \right)^{\frac{2\alpha_i \mu_i}{\Gamma_i^2}}$$
$$G_2(t) = \frac{\alpha - \Phi_i}{\Gamma_i^2} - \frac{2\Phi_i e^{t\Phi_i}}{\Gamma_i^2(\theta_i - e^{t\Phi_i})}$$

where

$$\Phi_i = \sqrt{\alpha_i^2 + 2\Gamma_i^2}$$
$$\theta_i = \frac{\alpha_i + \Phi_i}{\alpha_i - \Phi_i}.$$

A.4 Solving H

Recall that for each $i = 1, ..., n$

$$H(\xi_i, t) = \mathsf{E}^Q \left[\xi_i(t) \exp\left(- \int_0^t \xi_i(s) ds \right) \right].$$

Applying Itô's formula to the discounted prices also denoted by $H(\xi_i(t), t)$, we get that

$$dH = H_t dt + H_{\xi_i} d\xi_i + \frac{1}{2} H_{\xi_i \xi_i} < d\xi_i, d\xi_i > .$$

Hence,

$$dH = H_t dt + (\alpha(\mu_i - \xi_i(t))dt + \sqrt{\xi_i(t)} dB_i(t)) H_{\xi_i} + \frac{\Gamma_i^2}{2} H_{\xi_i \xi_i} dt - \xi_i H dt.$$

Under Q, the discounted prices $H(\xi_i(t), t)$ are martingales, so we need that

$$\frac{\Gamma_i^2}{2} \xi_i(t) H_{\xi_i \xi_i} + \alpha_i(\mu_i + \xi_i(t)) H_{\xi_i} + H_t - \xi_i(t) H = 0$$

subject to the boundary condition $H(\xi_i, 0) = \xi_i$.

Once again, we decompose

$$H(\xi_i, t) = (H_1(t) + H_2(t)\xi_i) \exp(G_2(t)\xi_i).$$

Then, for the partial differential equation to be satisfied, $H_1(t)$, $H_2(t)$ need to fulfill the Riccati equations

$$\frac{H_2'(t)}{H_2(t)} - \alpha_i + (\Gamma_i^2 + \alpha_i \mu_i) G_2(t) = 0$$
$$H_1'(t) + \alpha_i \mu_i H_1(t) G_2(t) + \alpha_i \mu_i H_2(t) = 0$$

subject to the initial conditions $H_1(0) = 0$ and $H_2(0) = 1$. Observe that these are the same equations than the ones we have for $G_1(t)$ and $G_2(t)$ with again $\Gamma_i = b$, $\alpha_i = a$, $\mu_i = m$ and $\gamma_i = 1$. Therefore, the solution is given by

$$H_1(t) = \frac{\alpha_i \mu_i}{\Phi_i} (e^{\Phi_i t} - 1) \exp\left(\frac{-\alpha_i \mu_i (\alpha_i - \Phi_i) t}{\Gamma_i^2} \right) \left(\frac{\theta_i - 1}{\theta_i - e^{\Phi_i t}} \right)^{\frac{2\alpha_i \mu_i}{\Gamma_i^2} + 1}$$
$$H_2(t) = \exp\left(\frac{-\alpha_i \mu_i (\alpha_i - \Phi_i) t}{\Gamma_i^2} + \Phi_i t \right) \left(\frac{\theta_i - 1}{\theta_i - e^{\Phi_i t}} \right)^{\frac{2\alpha_i \mu_i}{\Gamma_i^2} + 2}.$$

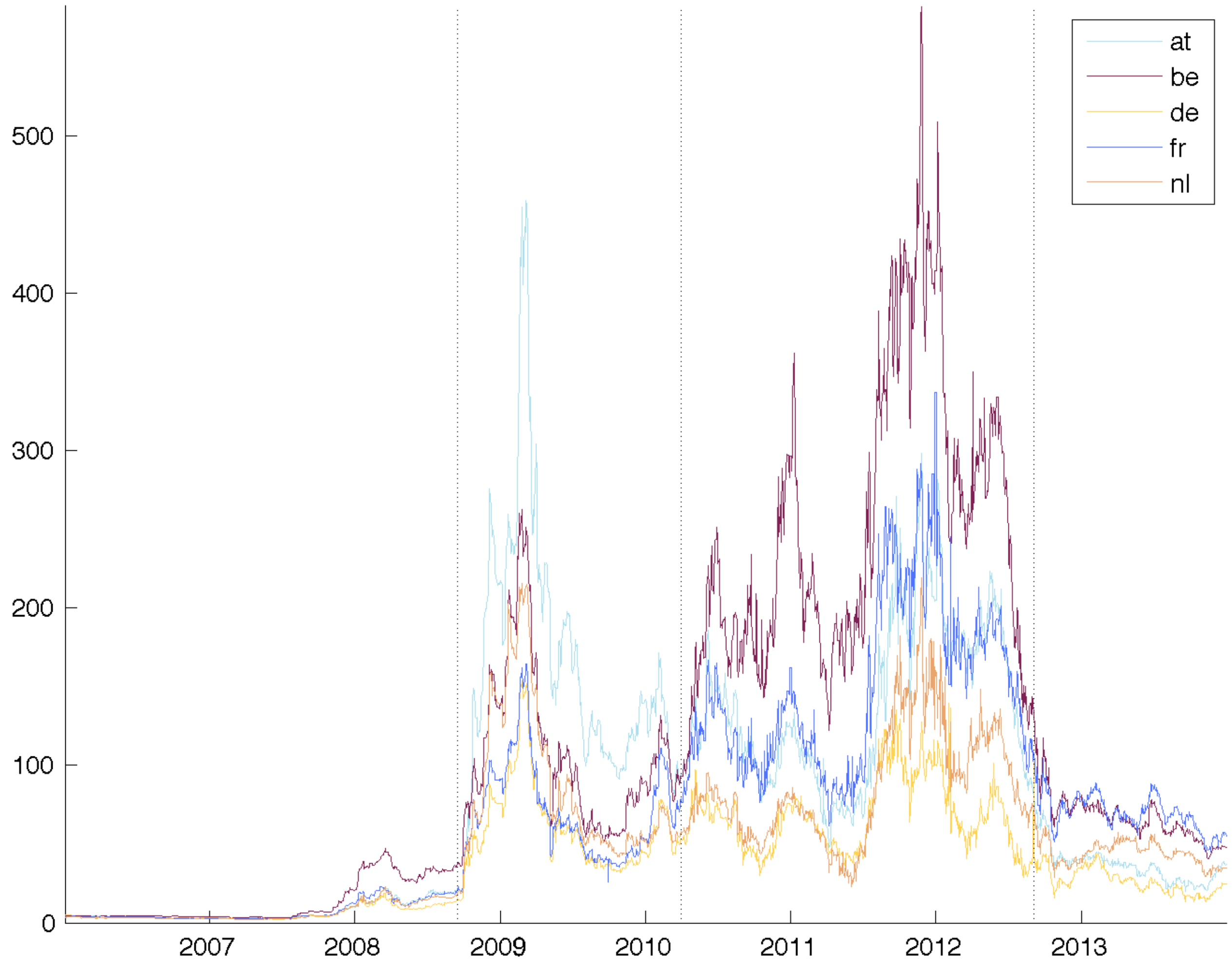
B Sample description

Table 3: List of banks included in the sample

Country	Name of the institution
Austria	BAWAG P.S.K. (WAG)
	Erste Bank Group (ERS)
	Raiffeisen Bank International (RAI)
Belgium	Fortis N.V. / Ageas Holding N.V. (FOR)
	KBC BANK (KBC)
France	AXA France (AXA)
	Banque Fédérative du Crédit Mutuel (BQE)
	Banque PSA Finance (PEU)
	BNP Paribas (BNP)
	Crédit Agricole (AGR)
	Crédit Industriel et Comercial (CIC)
	Crédit Lyonnais (LYO)
	Dexia Crédit Local (DEX)
	Gecine (GEC)
	Klépierre (KLE)
	Société Générale (SOC)
	Sophia GE (SOP)
	Wendel (WEN)
Germany	Allianz AG (ALL)
	Deutsche Bank AG (DBA)
	Commerzbank AG (COM)
	DZ Bank (DZB)
	HSH Nordbank (HSH)
	Landesbank Baden-Württemberg (LBW)
	Bayerische Landesbank (BLB)
	Landesbank Berlin (LBB)
	Landesbank Hessen - Thühringen (LHT)
	Münchner Rčkversicherung (MRV)
	Norddeutsche Landesbank (NLB)
	Hypo Real Estate Holding AG (HRE)
	West LB / Portigon AG (WLB)
Greece	EFG Eurobank Ergasias S.A. (EFG)
	National Bank of Greece (NAT)
Ireland	Irish Life and Permanent(ILP)
	Anglo Irish Bank(ANG)
	Depfa PLC (DEP)
	Governor and Company of the Bank of Ireland (GOV)
	Irish Nationwide Bank (NAT)

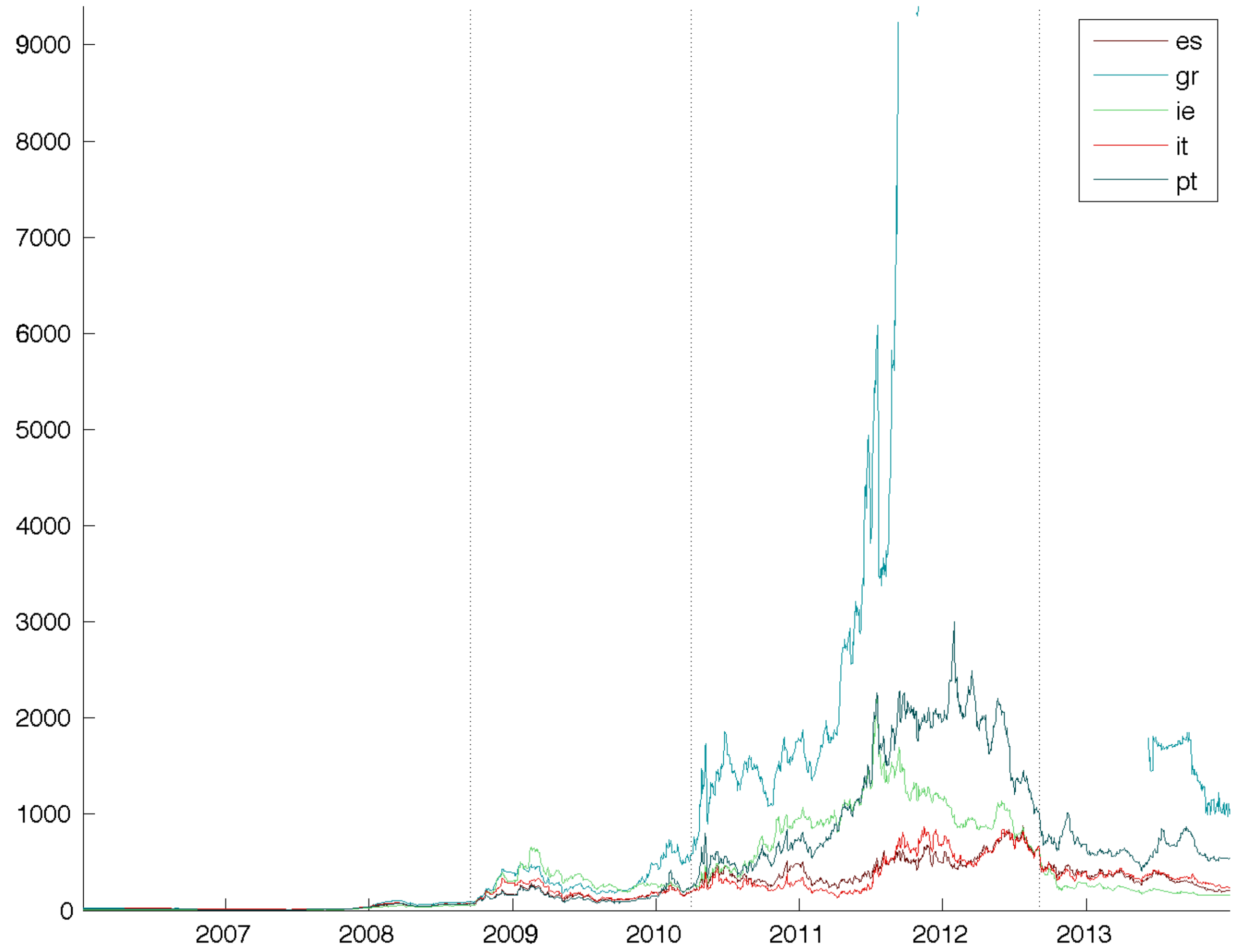
Country	Name of the institution
Italy	Assicurazioni Generali (ASG)
	Banca Nazionale de Lavoro (LAV)
	Banca Italease S.p.A. (LEA)
	Intesa Sanpaolo S.p.A (INT)
	Mediobanca S.p.A. (MED)
	Banca Popolare di Milano (MIL)
	Banca Monte dei Paschi di Siena S.p.A (MPS)
	Banco Popolare S.C.(POP)
	Unione di Banche Italiane SCPA (UDP)
	UniCredit S.p.A. (UNI)
Netherlands	Ing Bank NV (ING)
	Abn Amro Bank NV (ABN)
	Achmea Holding NV (ACH)
	Aegon NNV (AEG)
	NIBC Bank NV (NIB)
	Rabobank (RAB)
	Rodamco Europe NV (ROD)
	SNS Bank NV (SNS)
	F. van Lanschot Bankiers NV (VAN)
Portugal	Caixa Geral de Depositos, SA (CAI)
	Banco Comercial Portugues, SA (BCO)
	Espirito Santo Financial Group, SA (SAN)
	Banco Portugues de Investimiento (BPI)
Spain	Banco Santander S.A. (SAN)
	Banco Bilbao Vizcaya Argentaria S.A. (BBV)
	Caja de Ahorros y Pensiones de Barcelona (CAB)
	Caja de Ajorros del Mediterraneo (MED)
	Caja de Ahorros y Monde de Piedad de Madrid (MPM)
	Banco Popular Espanol, S.A. (POP)
	Banco de Sabadell, S.A. (SAB)
	Caixa de Ahorros de Valencia, Castelln y Alicante / Bancaja (CAV)
	Bankinter, S.A. (INT)
	Banco Pastor, S.A. (PAS)

Figure 1: Instantaneous risk-neutral default intensities processes for core countries



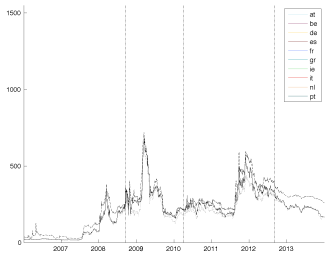
The figure shows the time series of sovereign default intensities for core countries bootstrapped from CDS prices of 1-year, 3-year, 5-year, 7-year and 10-year maturity using the corresponding risk-neutral rates. The intensity is measured in basis points.

Figure 2: Instantaneous risk-neutral default intensities processes for periphery countries.

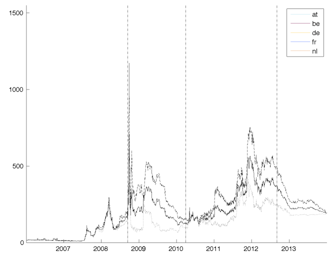


The figure shows the time series of sovereign default intensities for core countries bootstrapped from CDS prices of 1-year, 3-year, 5-year, 7-year and 10-year maturity using the corresponding risk-neutral rates. The intensity is measured in basis points.

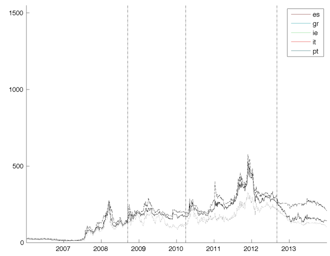
Figure 3: Quantiles of idiosyncratic default intensity of banks per country



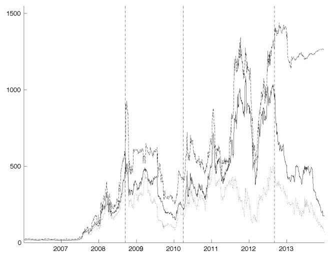
(a) Austria



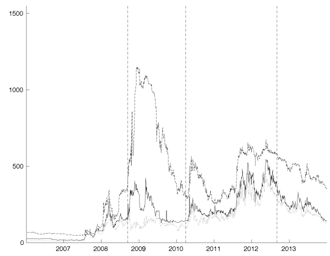
(b) Belgium



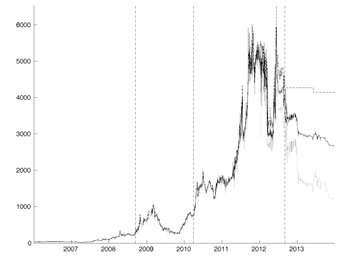
(c) Germany



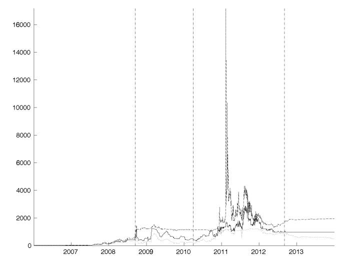
(d) Spain



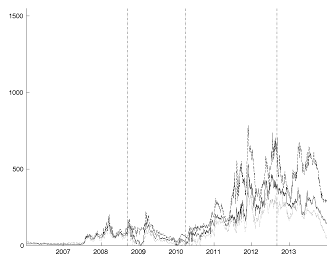
(e) France



(f) Greece

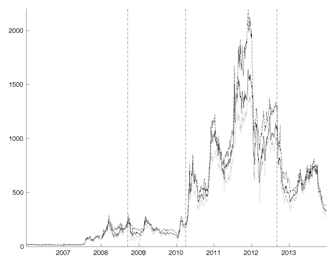


(g) Ireland



(h) Italy

(i) Netherlands



(j) Portugal

Quantiles of risk-neutral bank default intensities per country. This figure shows quantiles for instantaneous default intensities for all banks in a certain country bootstrapped from CDS spreads of 1-year, 3-year, 5-year, 7-year and 10-year maturity and corresponding risk-neutral rates. All intensities are measured in basis points.

Table 4: Summary statistics of 5-year sovereign CDS spreads

	Mean	Std. Dev.	Min.	Med.	Max.
Austria	48.93	48.44	1.49	31.45	268.88
Belgium	66.23	66.34	1.93	43.13	339.34
Germany	23	19.42	1.29	20.8	91.38
Spain	136.64	119.6	2.35	118.38	504.15
France	43.19	38.89	1.47	39.36	198.68
Greece	4479.1	8464.07	4.72	281.83	23571.96
Ireland	217.71	237.64	1.67	140.2	1193.98
Italy	137.96	122.89	5.29	117.86	501.52
Netherlands	31.32	27.81	1.13	28.14	129.95
Portugal	296.53	352.53	3.86	129.46	1554.03

Table 5: Summary statistics of 5-year bank CDS spreads

		Mean	Std. Dev.	Min.	Med.	Max.
Austria	**25th perc.**	145.92	95.55	9.95	146.8	464.02
	median	148.15	98.35	10.1	151.46	503.73
	75th perc.	162.67	98.63	15.9	175.77	550.42
Belgium	**25th perc.**	100.74	69.31	5.12	104.46	512.95
	median	129.76	93.25	5.79	129.21	591.08
	75th perc.	158.78	117.2	6.47	153.95	669.2
Germany	**25th perc.**	94.81	51.46	5.81	101.26	229.06
	median	103.7	64.42	6.2	107.62	333.77
	75th perc.	115.72	74.85	7.79	121.42	364.41
Spain	**25th perc.**	178.61	131.94	7.77	195.94	531.31
	median	292.74	235.32	9.76	269.41	888.94
	75th perc.	396.13	316.54	11.75	392.37	1386.94
France	**25th perc.**	116.23	85.02	5.97	108.12	397.75
	median	131.83	99.76	6.62	114.5	451.76
	75th perc.	296.42	234.2	26.68	265.79	974.6
Greece	**25th perc.**	700.99	722.65	11.44	412.6	2790.54
	median	787.08	796.01	12.92	435.97	2813.17
	75th perc.	873.17	869.38	14.4	459.34	2835.8
Ireland	**25th perc.**	405.1	282.33	7.82	302.16	1030.76
	median	443.16	417.36	8.73	387.88	2032.86
	75th perc.	628.01	602.98	11.53	524.89	3139.61
Italy	**25th perc.**	148.73	131.73	6.4	114.38	580.86
	median	173.67	154.33	7.18	122.93	694.64
	75th perc.	238.68	230.25	11.87	135.02	917.59
Netherlands	**25th perc.**	100.54	65.7	4.37	101.05	274.31
	median	129.52	85.51	8.97	110.9	341.78
	75th perc.	163.39	109.8	19.86	193.8	621.66
Portugal	**25th perc.**	329.17	326.73	8.35	152.52	1191.64
	median	348.72	343.68	8.67	155.47	1285.69
	75th perc.	378.7	402.25	9.27	164.96	1651.8