Systemic Risk in the European Sovereign and Banking System

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Abstract

This paper investigates the systemic risk of the European sovereign and banking system during 2008–2013. Our systemic risk measure can be intuitively interpreted as the conditional joint probability of default of an entity, given the hypothetical default of other entities. Our measure not only reflects individual default risk characteristics but also captures the underlying interdependent relations between sovereigns and banks in a true multivariate setting. Our results reveal significant time variation in distress dependence and systemic risk spillover effects for the sovereign and banking system. In particular, we show that peripheral sovereigns and banks have greatly increased in systemic importance, leading to intensified systemic relations between the peripheral and the core. Based on our measure, the systemic risk of the combined sovereign and banking system reached historical highs of 32% during the sovereign debt crisis. We find that this heightened risk is mainly driven by the default risk premium and the sovereign risk premium coupled with a steady increase in physical default risk.

Keywords: Systemic risk, Sovereign default, Banking stability, Tail risk

JEL Classification: C16, C61, G01, G21

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1. Introduction

One of the most critical issues in current debates is the looming possibility of a sovereign default in the euro area (EA). Regulators and policymakers fear that vulnerabilities in the peripheral European countries – namely, Greece, Ireland, Italy, Portugal, and Spain – could potentially spread to the rest of Europe. At the same time, European leaders are wrestling with the prospect of the failure of systemically important banks and its consequences on the European banking system. With the rise of the sovereign debt crisis, the interdependence between sovereigns and banks has greatly intensified, causing fears of negative feedback loops between the two systems. Against this backdrop, the need for identifying the level of systemic risk becomes increasingly apparent. This paper addresses the issue by utilizing a conditional measure of systemic risk to quantify the effects of sovereign and bank default on the European sovereign and banking system.

Although there is no universal definition of systemic risk, a recurring theme throughout the systemic risk literature is that true systemic events impact the entire financial system (Billio, Getmansky, Lo, & Pelizzon, 2012). At its core, systemic risk is associated with the risk that arises due to the *interdependence* between financial entities. From this perspective, systemic events do not necessarily have to stem from a causal origin. For example, Sandleris (2014) finds that sovereign defaults can affect the private sector even if domestic agents do not hold any of the defaulted instruments. Morrison and White (2013) show that systemic interbank crises could simply be a result of a common regulation framework. Therefore, we construct a measure of systemic risk that reflects the contribution of the interdependence of an entity to the overall systemic default risk of the system. Our measure of systemic risk can be intuitively interpreted as the conditional joint probability of default of an entity, given the (hypothetical) default of other entities within the system. The advantage of using a conditional measure is that it not only captures an entity's individual default risk characteristics but also reflects the dynamics of its joint default risk due to its interdependence with other entities.

There are two main features of our systemic risk measure. First, a major factor in our measure is marginal probabilities of default, which are derived from bootstrapping credit default swap (CDS) spreads. We use CDS contracts because they are forward looking and they readily incorporate investors' perceptions of default risk since CDS markets react instantly to changes in credit risk. Furthermore, systemic risk measures based on CDS spreads are generally superior to those derived from interbank rates or equity prices (Rodríguez-Moreno & Peña, 2013). Second, we ensure that our systemic risk measure is applicable in a true multivariate setting consisting of both sovereigns and banks. This is accomplished by using the consistent information multivariate density optimization (CIMDO) methodology introduced by Segoviano (2006). Since joint default risk is not traded, we explicitly derive a time-varying dependence structure in the form of a multivariate probability distribution from which we estimate joint probabilities of default. This approach allows us to study the full extent of systemic default risk, since it grants us immense flexibility in the choice of conditioning.

Our focus on the European sovereign and banking system is not coincidental but is motivated by the extensive interconnections between them. Until recently, there had been no credit risk for sovereign debt in developed countries for many years. Prior to the global financial crisis of 2007–2009, most European banking regulation focused on individual banks and the risk on their balance sheets. This form of regulation turned out to be flawed, since it ignores the systemic relation between the sovereign and banking systems. For example, Gerali, Neri, Sessa, and Signoretti (2010) show that the largest contribution to the contraction of EA economic activity in 2008 had been due to shocks originating from the banking sector. The onset of the sovereign debt crisis saw the relation between banks and sovereigns escalate to a new level. The Greek default in 2011 showed that there is credit risk in holding sovereign debt. Among the bailout packages were substantial write-offs of Greek debt in the books of private investors, most of which were held by banks. As the sovereign debt crisis evolved, European banks were confronted with liquidity dry-ups and stress in their capital positions. The European Banking Authority's (EBA) stress test results in 2011 revealed that banks in peripheral sovereigns were unlikely to weather negative shocks to the sovereign system, given their sovereign debt exposure. Overall, the combined effect of the vulnerability of certain sovereigns and the continued stress in the banking system meant that the financial conditions of banks and sovereigns had become increasingly intertwined.

The main findings of this paper can be summarized as follows. First, we show that our measure of systemic risk is successful in quantifying the level of systemic risk of the sovereign system. During the height of the sovereign debt crisis, the conditional joint probability of default of the sovereign system, given the default of core sovereigns such as Germany, reached maximum values of 47% while the default of peripheral sovereigns such as Italy and Spain produced lower values of 30%. We also show that peripheral sovereigns are the least resilient to system-wide defaults, since their conditional joint probabilities of default reached 100% during the sovereign debt crisis. In addition, we document a significant amount of systemic risk spillover from peripheral sovereigns to the core. Specifically, part of the increased systemic relation between the peripheral and the core can be attributed to the increasing levels of systemic risk within the peripheral sovereign system, while another part is due to the cascade effects between the peripheral and the core.

Second, we find that the banks of certain sovereigns played unique roles during recent periods. Of the EA banks, French banks contributed the most to the systemic risk of the banking system, both jointly and individually, during the global financial crisis and the sovereign debt crisis. However, banks in Italy and Spain were not far behind in terms of systemic importance, since their systemic risk contributions increased rapidly during the sovereign debt crisis. Banks in non-EA sovereigns, such as the United Kingdom and Switzerland, were the most important in maintaining the stability of the European banking system during the sovereign debt crisis. At the individual bank level, we show that the biggest contributors to the systemic risk of the banking system often coincide with the biggest banks in each sovereign. This result supports the 'too-big-to-fail' concern from a macroprudential perspective.

Third, we show that in the combined sovereign and banking system, the evolution of our systemic risk measure corresponds with major systemic events that occurred throughout our sample period. In particular, we demonstrate that the systemic risk of the multivariate system reached unprecedented levels during the sovereign debt crisis as the conditional joint probability of default of the banking system, given the default of Germany, reached historical highs of 32%. In decomposing systemic risk, we show that much of this heightened increase in systemic risk is due to rapid increases in the default risk premium and the sovereign risk premium coupled with a steady increase in physical probabilities of default.

This paper is closely connected with two strands of the literature. The first strand focuses on the measurement of systemic risk. Recent developments in this field include Acharya, Pedersen, Philippon, and Richardson (2010), Adrian and Brunnermeier (2011), Brownlees and Engle (2012), Huang, Zhou, and Zhu (2009), López-Espinosa, Moreno, Rubia, and Valderrama (2012), Girardi and Ergün (2013), and Puzanova and Düllmann (2013). A comprehensive overview can be found in Bisias, Flood, Lo, and Valavanis (2012). The common theme among these studies is the estimation of the magnitude of losses conditional on the simultaneous distress of other institutions. Conceptually, our approach is related to Acharya et al.'s (2010) marginal expected shortfall, Adrian and Brunnermeier's (2011) conditional value at risk, and Huang et al.'s (2009) distress insurance premium, where the marginal expected shortfall can be interpreted as the average losses of a particular institution when the returns on the entire market fall below a certain threshold, the conditional value at risk measures the value at risk of the financial system conditional on the distress of other institutions, and the distress insurance premium measures the hypothetical insurance premium required to cover distressed losses in the banking system. The main difference between these three measures and ours is that our measure of systemic risk is not characterized in terms of losses but are conditional joint *probabilities* of default.

By using a probabilistic measure, our approach has several advantages over the aforementioned measures. Specifically, the preceding measures lack a forward-looking focus, since they predominantly rely on historical stock market returns and firm-specific data. While this approach may appear to capture systemic exposures, it only does so to the degree that systemic losses are well represented in the historical data. Consequently, extremely rare events that belong in the tail of the tail of market risks are unlikely to be captured. To overcome this deficiency, we directly examine tail risk by using CDS spreads that are extremely sensitive to an institution's creditworthiness. Our procedure effectively captures the default risk perceptions of market participants and ensures that future distress expectations and systemic shocks are embedded in our systemic risk measure. The previously mentioned measures also suffer from a restrictive definition of default; that is, an institution is defined to be in default if its returns fall below a certain threshold. When applied in a sovereign and banking context, this type of conditioning provides a narrow perspective. Contrarily, one of the most important features of our *conditional* measure of systemic risk is its flexibility in conditioning. Our procedure enables us to investigate many aspects of systemic risk, including individual and combined systemic default risk, intra-system systemic risk, and inter-system systemic risk.

Another advantage of our approach is in our handling of sovereign default risk. Most approaches in estimating sovereign credit risk rely on the basic premise of the structural model (Merton, 1974). Papers that employ this technique include Bartram, Brown, and Hund (2007), Gray, Merton, and Bodie (2007), and Lehar (2005). However, the main drawback of these studies is the specification of an institution's capital structure. Structural models are overwhelmingly difficult to apply in a sovereign context because explicit definitions of sovereign assets and liabilities are needed. Furthermore, inputs under the structural model include the value of sovereign assets and the knowledge of sovereign asset return distributions, neither of which are directly observable. We overcome these shortcomings by applying the CIMDO methodology. In essence, we shift the focus away from capital structure and directly view the sovereign and banking system as a joint distribution of its constituent entities. To capture tail risk, the CIMDO methodology adjusts the tail region of the underlying joint distribution so that it is always consistent with empirical data. Consequently, our measure of systemic risk is applicable in a multivariate setting because we circumvent the issue of having to define sovereign capital structure. In addition, the CIMDO methodology naturally encompasses an updating process that allows us to constantly revise our views on default risk by relying on changes in market default risk perceptions. Thus, we are able to capture all interactions and co-movements between every entity within the system at each point in time.

The second strand of literature related to our paper examines the systemic risk of sovereigns and banks. Our paper is positioned at the intersection of these studies, that is, we are particularly concerned with the systemic risk *between* sovereigns and banks. On the sovereign side, recent research concentrates on the relationship between sovereign credit risk and common global and financial market factors (see, e.g., Ang & Longstaff, 2013; Bhanot, Burns, Hunter, & Williams, 2014; Caporin, Pelizzon, Ravazzolo, & Rigobon, 2013; Gande & Parsley, 2007; Haidar, 2011; Longstaff, Pan, Pedersen, & Singleton, 2011; Pan & Singleton, 2008). On the bank side, the extensive literature typically focuses on situations in which multiple financial institutions fail as a result of a common shock. A broad overview of the topic can be found in Allen, Babus, and Carletti (2009). Papers involving both the sovereign and banking systems generally focus on the contagion between sovereign and bank default risk rather than measuring the level of systemic risk between the two. These papers are relatively scarce, since they only recently began to gain prominence during the sovereign debt crisis. The majority of studies in this area examine the contagion between sovereigns and banks by using co-movements between financial variables, these being CDS spreads most of the time (see, e.g., Acharya, Drechsler, & Schnabl, 2013; Alter & Beyer, 2013; Alter & Schuler, 2012; Angeloni & Wolff, 2012; Bruyckere, Gerhardt, Schepens, & Vennet, 2013; Ejsing & Lemke, 2011). A notable exception is a recent paper by Correa, Lee, Sapriza, and Suarez (2014), who explicitly focus on the effect of sovereign rating changes on banks and provide empirical evidence that sovereigns and domestic banks are markedly interconnected through government guarantees. Our paper adds to this literature by *quantifying* the level of systemic risk in the combined sovereign and banking system and by tracking its evolution throughout the global financial crisis and the sovereign debt crisis.

The remainder of the paper is organized as follows. Section 2 outlines the methodology for constructing and estimating the conditional joint probability of default. Section 3 summarizes the data. Section 4 presents the empirical results and Section 5 concludes the paper.

2. Methodology

2.1. Deriving the Conditional Joint Probability of Default

The definition of systemic risk is not well defined throughout the literature and, as a result, can be measured from a wide range of perspectives. We follow the view that systemic risk can be quantified through probabilistic measures in both the sovereign and banking systems (Radev, 2012). We begin by constructing the system's marginal probability of default (PoD). Assume there are n entities (or institutions) in the system and let $X_1, X_2, \cdots, X_n$ denote the random variables corresponding to the natural logarithm of assets of institution $I_1, I_2, \cdots, I_n$, respectively. Reminiscent of the structural approach, we define an institution to be in default if its logarithm of assets exceeds a certain threshold, which we denote $X_d^{I_i}$. The marginal probability of default is given by[1]

$$PoD_{I_i} = P\left(X_i \geq X_d^{I_i}\right) = \int_{-\infty}^{\infty} \cdots \int_{X_d^{I_i}}^{\infty} \cdots \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x_1, x_2, \cdots, x_n) dx_1 dx_2 \cdots dx_i \cdots dx_n \tag{1}$$

where $p(x_1, x_2, \cdots, x_n)$ is the joint probability density function describing the n-dimensional system.

The above definition gives the *theoretical* probability of default of institution I_i. However, since the underlying asset structure of an institution evolves stochastically throughout time, the default threshold will also change throughout time. Following Segoviano (2006), we define the fixed time average default threshold of institution I_i as

$$X_d^{I_i} = \Phi^{-1}\left(1 - \overline{PoD_{I_i}}\right) \tag{2}$$

where $\Phi^{-1}(\cdot)$ denotes the standard inverse normal cumulative function and $\overline{PoD_{I_i}}$ is the time average *empirical* probability of default of institution I_i, estimated by bootstrapping CDS spreads. Since the default threshold is fixed, we vary the underlying probability distribution throughout time so that each point in time is described by a unique density function.

The next step is to calculate the joint probability of all entities simultaneously suffering large losses. We define the joint probability of default (*JPoD*) of n entities as

$$\begin{aligned} JPoD_{\{I_1, I_2, \cdots, I_n\}} &= P\left(X_1 \geq X_d^{I_1}, X_2 \geq X_d^{I_2}, \cdots, X_n \geq X_d^{I_n}\right) \\ &= \int_{X_d^{I_n}}^{\infty} \cdots \int_{X_d^{I_2}}^{\infty} \int_{X_d^{I_1}}^{\infty} p(x_1, x_2, \cdots, x_n) dx_1 dx_2 \cdots dx_n \\ &= JPoD_{system} \end{aligned} \tag{3}$$

By construction, $JPoD_{system}$ is an unconditional measure, since it does not explicitly account for the negative spillover effects of default but, rather, reflects the system's fragility to default shocks.

We now combine the marginal probability of default and the joint probability of default through Bayes' theorem to produce the conditional joint probability of default (*CoJPoD*)

[1] For convenience, the default region is defined to be in the right tail of the density function.

of the system given the default of institution I_k:

$$
\begin{aligned}
&CoJPoD_{\{I_1,\cdots,I_{k-1},I_{k+1},\cdots,I_n\}|I_k} \\
&= CoJPoD_{\{system\backslash I_k\}|I_k} \\
&= P\left(X_1 \geq X_d^{I_1}, \cdots, X_{k-1} \geq X_d^{I_{k-1}}, X_{k+1} \geq X_d^{I_{k+1}}, \cdots, X_n \geq X_d^{I_n} | X_k \geq X_d^{I_k}\right) \\
&= \frac{JPoD_{\{I_1,I_2,\cdots,I_n\}}}{PoD_{I_k}} \\
&= \frac{JPoD_{system}}{PoD_{I_k}}
\end{aligned} \tag{4}
$$

This expression shows that $CoJPoD_{\{system\backslash I_k\}|I_k}$ is the default likelihood of the remaining institutions within the system given the default of a particular institution. It can be computed as the ratio of the system's joint probability of default to the marginal probability of default of a particular institution. We can interpret $CoJPoD_{\{system\backslash I_k\}|I_k}$ as the contribution of institution I_k's default on the system's overall systemic risk.

The term *CoJPoD* is a measure of systemic risk due to interdependence rather than causality; this is an ideal property to have when attempting to quantify systemic risk. For instance, the failure of a few entities may not be systemic, but the failure of a single highly interconnected entity can be. In other words, the default of a group of entities may not necessarily *cause* the rest of the system to default. However, if the default was a result of a common factor, then the rest of the system will be more likely to default due to the systemic nature of the initial shock. Therefore, in the absence of causality, each individual entity's default risk should co-vary with the rest of the system's default risk due to the underlying interdependent relations between the entities. The *CoJPoD* measure captures this subtle aspect of systemic risk.

2.2. Estimating Marginal Probabilities of Default

The first ingredient of *CoJPoD* consists of deriving each entity's marginal probability of default. The structural approach is commonly used to model an institution's default risk. Under this approach, an institution's asset value is assumed to evolve stochastically over time and default is triggered by a drop in the institution's asset value below a certain threshold. However, the structural approach is inapplicable in a multivariate context consisting of both banks and sovereigns, since asset returns and asset correlations are not observed; even if they were, the question still remains as to what constitutes sovereign assets. To overcome this restriction, we follow Goodhart and Segoviano (2009), whereby we do not take a stance on what default actually entails but, rather, rely on market expectations of default to derive marginal probabilities of default. Specifically, we extract empirical probabilities of default from CDS spreads by applying the bootstrapping procedure outlined in Hull and White (2000). As a result, we circumvent the difficulty of defining unobservable asset returns.[2] There are four main advantages in using CDS spreads to estimate probabilities of default. First, estimation of PoD values from CDS spreads is not subject to the modelling of the distribution of asset values or the explicit estimation of asset correlations. Second, CDS spreads provide timelier market-based valuations, since CDS markets react to changes in default expectations in real time (Bruyckere et al., 2013). Third, CDS spreads are forward looking, in the sense that they frequently anticipate rating changes and closely track future fiscal deficits. Finally, CDS spreads are less affected by liquidity and flight-to-safety issues when compared to Treasury bonds.

The bootstrapping procedure that we utilize requires three main inputs: CDS maturities, discount rates, and recovery rates. We use daily CDS spreads with maturities of one to five years and daily AAA EA sovereign bond yields with maturities of three months to five years for the discount rates. As discussed below, the discount rates are treated as risk-free rates, since the bootstrapped probabilities of default are risk-neutral measures.[3] Following prior literature, we set a constant recovery rate of 40% (Sturzenegger & Zettelmeyer, 2008). The bootstrapping procedure begins with an iterative process whereby we assume a constant hazard rate function and build a probability curve using the CDS contract with the shortest maturity (one year). From this, we extend the probability curve to the CDS contract with the next longest maturity (two years), again assuming a constant hazard rate function. We continue this process until we reach the CDS contract with the longest maturity (five years). At each step of the recursive process, we ensure that the no-arbitrage condition is satisfied by equating the premium leg with the payoff leg.[4]

[2] Note that we do *not* use Eq. (1) to compute marginal probabilities of default, since the underlying asset processes are unobservable. However, as seen in Section 2.3, Eq. (1) is a constraint that must be satisfied when solving for the underlying joint probability density function.

[3] The AAA EA sovereign bond yields are obtained from the European Central Bank's (ECB) index of AAA-rated sovereign bonds of the EA sovereigns. To ensure that the sovereign bond yields are appropriate proxies for risk-free rates, we verify that none of the reference entities of the sovereign CDS contracts are used in the construction of the index.

[4] A CDS contract has two legs: a premium leg and a payoff leg. The former is the premium that buyers

Consequently, because the recovered term structure of hazard rates is arbitrage free, we obtain risk-neutral probabilities of default. In other words, the probabilities of default not only reflect physical probabilities of default but also contain information on any associated risk premium components. We take full advantage of this property when examining the decomposition of *CoJPoD*. We annualize the *PoD* values to align with the one-year horizon of interest of policymakers.

2.3. Estimating the Multivariate Joint Distribution

The bootstrapped *PoD* values represent individual default risk perceptions. We now implement a procedure that transforms these marginal probabilities of default into joint probabilities of default by imposing a dynamic dependence structure between the individual entities of the system. There are numerous approaches to modelling joint default risk (see, e.g., Avesani, Pascual, & Li, 2006; Bams & Wielhouwer, 1999; Cai, Einmahl, Haan, & Zhou, 2014; Lucas, Schwaab, & Zhang, 2014). However, most of them involve the calibration of dependence structures that rely on the evolution of an institution's capital structure. In a true multivariate context consisting of banks and sovereigns, the value of sovereign assets is not directly observable.

In comparison, the CIMDO methodology (Segoviano, 2006) recovers multivariate joint distributions without taking any stance on the observability of sovereign assets. The key improvements of the CIMDO procedure over traditional risk models is that it captures both linear and non-linear distress dependencies between entities in the system and allows for these to change throughout time, reflecting the fact that dependence differs during tranquil times and periods of distress. The underlying idea of the CIMDO approach is that any multivariate density that characterizes the stochastic behaviour of a group of random variables can be broken into two subsets of information: (1) the marginal distribution of each random variable and (2) the underlying dependence structure between random variables. To recover the latter, instead of assuming parametric distributions to fit available information, the CIMDO approach uses all available data to calibrate a non-parametric distribution. Such an approach minimizes the possibility of misspecification

pay to insure themselves against possible defaults of the reference entity. The latter represents the payoff to buyers in the case in which the reference entity defaults. The payoff equals the difference between the face value of the reference entity and its recovered value. If the reference entity does not default over the maturity of the CDS contract, the payoff is zero.

and ensures that the resulting distribution is always consistent with empirical data.

We begin by specifying a prior (or ex ante) joint density function to describe the underlying dependence structure between the entities within the system. We then update the prior by inferring indirect and partial information from the bootstrapped PoD values. This involves adjusting the probability mass in the tails of the prior density function such that its tail probability is consistent with the marginal probabilities of default. We continue this iterative process by updating the prior density function on a daily basis. The resulting posterior (or ex post) density function exhibits fat tail properties and is dynamic by construction. An important facet of this approach is that we do not have to explicitly specify what constitutes sovereign assets or liabilities when quantifying sovereign default risk. Since we effectively reverse-engineer the joint probability distribution describing the system, we simply rely on the bootstrapped probabilities of default to proxy for the system's underlying asset process. As a result, when Eq. (4) is used to compute conditional joint probabilities of default, each entity's marginal probability of default acts as a common denominator, allowing us to pool banks and sovereigns together to form a single multivariate system.[5] Section A.1 of the Appendix outlines the CIMDO procedure.

As Segoviano (2006) shows, using a multivariate standard normal distribution as the prior distribution is sufficient to explain the behaviour in the default region of the posterior distribution. Furthermore, the author demonstrates that the CIMDO methodology is highly robust to various prior distributions and employing more complex prior distributions such as the multivariate t-distribution or a mixture of normal distributions produces very similar tail regions in the posterior distribution. Thus, we choose the multivariate normal distribution as the prior distribution. Following Gorea and Radev (2014), we use a static variance–covariance matrix by estimating the sample correlation coefficients between the daily changes in the five-year CDS spreads of sovereign and bank CDS contracts.[6] We

[5] We pool banks and sovereigns together based on their marginal probabilities of default and *not* based on their CDS spreads. Indeed, treating banks and sovereign equally on the basis of their CDS spreads is counterintuitive, since their reference entities are two different types of economic entities, public and private. However, the unique setup of the CIMDO procedure allows us to form one multivariate system consisting of both banks and sovereigns. To see this, assume that the system's joint probability distribution is unknown but each entity's marginal probability of default is known. To recover the underlying joint probability distribution of the system, the CIMDO procedure pools together each entity's marginal probability of default and utilizes the CIMDO copula to derive the underlying dependence structure of the system, which is consistent with the marginal probabilities of default. As a result, allowing banks and sovereigns to appear simultaneously in Eq. (4) based on marginal probabilities of default is not problematic.

[6] The CIMDO methodology can use either a static or a dynamic variance–covariance matrix because

use a correlation structure based on risk, that is, CDS spreads, rather than one based on asset value, because the CIMDO procedure uses the marginal probabilities of default to proxy for the underlying asset process of the system, which then automatically updates the CIMDO copula whenever there are changes in individual probabilities of default. Therefore, the correct correlation structure to use when solving for the unknown posterior distribution is one that is based on risk rather than on asset value.[7]

To solve for the posterior distribution, we utilize the generalized cross-entropy (GCE) method (Botev & Kroese, 2011). Under this framework, our strategy translates to an optimization procedure whereby we reconcile the inconsistencies in the prior distribution such that it is as close as possible to the posterior distribution while satisfying the appropriate moment consistency constraints. The moment consistency constraints refer to restrictions of the form shown in Eq. (1), where we replace the theoretical probabilities of default with the bootstrapped *PoD* values. Finally, we use the Knullback–Leibler measure of cross-entropy to solve for the optimal posterior distribution. Section A.2 of the Appendix provides the solution to the CIMDO procedure under the GCE method. Our estimation procedure ensures that *CoJPoD* is updated in real time. Therefore, *CoJPoD* is neither an ex ante nor an ex post measure of systemic risk but, rather, a contemporaneous measure. As mentioned by Bisias et al. (2012), measuring systemic risk is not simply a matter of obtaining early warning signals for impending dangers; crisis response is also an important role for policymakers who are charged with systemic risk monitoring. Thus, the usefulness of *CoJPoD* lies in its ability to help monitor the ongoing state of the system and the identification of failing institutions and markets. Furthermore, since *CoJPoD* can be updated on a daily basis, it can provide valuable real-time signals of fragility in an emerging crisis.

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the CIMDO copula avoids the imposition of constant correlation parameter assumptions. Thus, employing a static variance–covariance matrix for our entire sample period does not detract from the dynamic and time-varying nature of the posterior distribution. Nevertheless, to ensure robustness, we replicate all analyses in the paper using a dynamic variance–covariance matrix. Specifically, we estimate a unique variance–covariance matrix at each point in time using the one-year rolling period correlation coefficients between the daily changes in the five-year CDS spreads of sovereign and bank CDS contracts. All of our results are very similar to those for the static variance–covariance case. The results are available upon request.

[7] Gapen, Gray, Lim, and Xiao (2008) measure sovereign correlation structure by using the correlation coefficients between each sovereign's estimated logarithms of asset values. The authors show that their measure is highly correlated with the CDS spreads of the respective sovereigns; hence, their correlation structure is unlikely to be different from ours.

2.4. Decomposition of the Conditional Joint Probability of Default

The variable *CoJPoD* is a risk-neutral measure of systemic risk because its input, *PoD*, is derived from an arbitrage-free model. Hence, we can decompose the systemic risk into physical (or objective) probabilities of default and risk premium components. Exploring these two elements simultaneously allows us to determine which component of *CoJPoD* is the dominating factor throughout our sample period. Kim, Loretan, and Remolona (2010) purport that, during periods of high volatility, the risk premium components tend to dominate CDS spreads. Given that CDS spreads are the main ingredient for constructing *CoJPoD*, our aim is to investigate how much of the variation in *CoJPoD* is determined by changes in the pure credit quality of institutions and how much is induced by market risk perceptions.

We use the distance to default (DTD) metric to proxy for physical probabilities of default. In a banking context, the DTD measures how far away an institution is from default in units of standard deviation. A large DTD value implies that the institution is far from default and is deemed to have a low physical probability of default. Estimation of the DTD requires knowing the market value of the assets and their volatility, both of which are unobservable. Details on how the DTD is computed can be found in Crosbie and Bohn (2003). The DTD measure bears a striking resemblance to the expected default frequency statistic provided by Moody's KMV. In fact, the DTD is a major component of the expected default frequency, but the latter also uses other inputs, such as historical default events, to transform the DTD into physical probabilities of default. We use the DTD to proxy for physical default probabilities, since it is a metric based solely on an institution's balance sheet items and therefore represents its pure credit quality.

Following Black, Correa, Huang, and Zhou (2013), we examine three prevalent risk premiums. First, we proxy for the default risk premium by computing the daily difference between the yields of 10-year euro zone industrials rated BBB and those rated AA+/AA (Chen, Collin-Dufresne, & Goldstein, 2009). Second, we proxy for the liquidity risk premium by using the daily three-month euro LIBOR/OIS (or EURIBOR/EONIA) spread (Brunnermeier, Crockett, Goodhart, Persaud, & Shin, 2009). Third, we proxy for the sovereign risk premium by computing the daily difference between Germany's 10-year generic yield and the average of the Spanish and Italian 10-year generic yields weighted by their quarterly real gross domestic products (GDPs). An important caveat is that EA governments and other international bodies often provide bailout packages and guarantees for the European banking system; consequently, senior CDS spreads will be adjusted downwards. Therefore, in our subsequent empirical analyses, marginal contributions from physical probabilities of default and risk premiums should be interpreted as lower bounds in the case of no government support.

3. Data

In July 2011, the EBA released the results of their stress tests for a broad range of 90 European banks from various countries around Europe, including Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Norway, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. This group of banks and sovereigns forms the starting point of our sample. We select banks and sovereigns based on strict liquidity criteria to ensure that CDS spreads reflect meaningful information on bank and sovereign credit risk. Specifically, each bank and sovereign must have informative CDS contracts for maturities of one to five years for the period 1 January 2008 to 31 December 2013. A CDS contract is informative during a certain quarter if at least 70% of its spread changes are non-zero during the quarter. We do not include banks or sovereigns that have non-informative CDS contracts. Our sovereign sample consists of all 14 sovereigns used in the EBA stress test, which can be decomposed as follows. We include 10 EA sovereigns, five of which are peripheral sovereigns (Greece, Ireland, Italy, Portugal, and Spain) and the remaining are core sovereigns (Austria, Belgium, France, Germany, and the Netherlands). We also include three European Union (EU) sovereigns (Denmark, Sweden, and the United Kingdom), since their economies play a big role in the stability of the EA. Finally, we include Norway, which is part of neither the EA nor the EU but is closely associated with the EU through its membership in the European Economic Area. Our bank sample consists of 40 banks out of the 90 used in the EBA stress test. We include banks with informative CDS contracts from all 14 sovereigns, with the exception of Norway, which does not have any banks with informative CDS contracts. In addition, we include banks from Switzerland but do not use Switzerland in our sovereign sample since its sovereign CDS contract is not informative enough for the majority of our sample period. Table 1 gives an overview of the banks and sovereigns used in our study.

Our sample period is from 1 January 2008 to 31 December 2013, allowing us to compare the level of systemic risk from the 2008 global financial crisis through to the recent European sovereign debt crisis. The beginning of the sample period is dictated by the availability of informative CDS data for all sovereigns and banks in the study. To avoid any ambiguity regarding the time period of these two crises, we follow Arghyrou and Kontonikas (2012) and define the global financial crisis as the start of our sample period to February 2010 and the sovereign debt crisis from March 2010 to the end of our sample period. The start date of the sovereign debt crisis coincides with the beginning of the European authorities' intervention in Greece. We use USD-denominated (EUR-denominated) senior CDS contracts with maturities of one to five years for sovereigns (banks). Daily CDS mid-rate spreads are obtained from CMA, Datastream. We prefer US dollar-denominated CDS contracts for sovereigns, since they are less likely to be affected by European credit events. Such contracts are also considerably more liquid than their EUR-denominated counterparts. For comparability between sovereign and bank CDS contracts, we set the euro as our base currency; thus, any CDS contracts denominated in US dollars will be transformed into a euro equivalent by using the historical daily euro–US dollar exchange rate obtained from Bloomberg.

With regards to our bootstrapping procedure, we proxy for discount rates by using the daily AAA EA government bond yields with maturities of three months to five years, obtained from the ECB's Statistical Data Warehouse. As part of the CIMDO procedure, we proxy for the sovereign correlation matrix by calculating sample correlation coefficients based on daily changes in the five-year CDS spreads of the sovereigns in our sample.[8] We choose a maturity of five years, since these CDS contracts are the most liquid and most actively traded contracts on the market. The correlation structure of the sovereign system is shown in Table 2. For the decomposition of systemic risk, the DTD data are obtained from the website of the Risk Management Institute at the National University of Singapore.[9] The data used to construct the default risk premium, the liquidity risk premium, and the sovereign risk premium are all obtained from Bloomberg.

[8]The correlation structure of the banking system and the combined sovereign and banking system is calculated similarly. For the sake of brevity, we do not report the correlation structure because the matrix is too large and does not convey any important information. However, the results are available upon request.

[9]The data can be accessed at `http://rmicri.org`.

4. Empirical Results

Our empirical analyses are organized as follows. First, we apply the methodology outlined in Section 2 to examine the level of systemic risk in the European sovereign system. We then investigate the systemic risk within the peripheral sovereigns and the systemic impact of peripheral sovereigns on the core sovereigns. Next, we explore the systemic risk of the European banking system and attempt to uncover the most systemically important banks. We then combine the sovereign and banking systems and examine the evolution of systemic risk in this multivariate system. Lastly, we study the decomposition of systemic risk into physical probabilities of default and risk premium components.

4.1. Systemic Risk in the European Sovereign System

We begin by investigating the two key ingredients of the *CoJPoD* measure, *PoD* and *JPoD*. Figure 1 presents the bootstrapped probabilities of default for the 14 sovereigns and the joint probability of default for the sovereign system. The sovereign default risk was virtually non-existent for all sovereigns at the beginning of our sample period, indicating that market participants had strong confidence in the ability of European sovereigns to finance their debt. All sovereigns experienced a peak in probabilities of default shortly after the Lehman Brothers' collapse in September 2008, but individual probabilities of default gradually decreased throughout 2009. The beginning of the sovereign debt crisis marked an upward trend in the probabilities of default of every sovereign. Peripheral sovereigns were perceived by investors to be the most likely to default, with Ireland and Portugal reaching probabilities of default of almost 20% in July 2011. At the extreme, the probability of default of Greece reached a plateau of 59% towards the end of our sample period due to a CDS credit event triggered for Greece in March 2012. On the other hand, core sovereigns such as Germany and the Netherlands were highly unlikely to default throughout the entire sample period. Similarly, Norway, Sweden, and the United Kingdom were largely unaffected by the sovereign debt crisis. The dynamics of the joint probability of default of the sovereign system is shown in the last panel of Fig. 1. During the global financial crisis, the joint probability of default reached a peak of 0.6%, indicating that the effects of the US financial crisis had rippled through to the European sovereign system. This peak was almost tripled towards the end of 2011, when the joint probability of default of the sovereign system reached 1.7%. In summary, the time-varying dynamics of *PoD* and *JPoD* show that the divergence in market expectations around individual sovereign defaults may not only be due to the inability of individual sovereigns to service their debts, but also be about the potential of the EA as a whole to support its members in need.

Figure 2 presents the conditional joint probability of default of the sovereign system given the default of each sovereign in our sample. The title of each panel is the sovereign that defaults. Compared to Fig. 1, the ordering is now reversed. Specifically, the conditional joint probability of default of the sovereign system is the highest throughout the sample period given the default of core sovereigns such as Germany and the Netherlands. The disparity between the systemic impact of core sovereigns defaulting compared to peripheral sovereigns defaulting is even more pronounced during the sovereign debt crisis. For example, in November 2011, the *CoJPoD* value of the sovereign system reached 47% given the default of Germany, whereas the default of the larger peripheral sovereigns, such as Italy and Spain, produced *CoJPoD* values of only 30%. This finding is consistent with the results obtained in Fig. 1. Market participants perceive core sovereigns to be the safest sovereigns; thus, given their default, one would expect a dramatic increase in the joint default risk of the remaining sovereigns. Similarly, investor confidence in peripheral sovereigns is very low; thus, their default would have little influence on the joint default risk of the sovereign system. Although these results confirm macroeconomic intuition, the benefit of our approach is that we are able to quantify the level of systemic risk given a sovereign default.

We now interchange the order of conditioning and calculate the conditional joint probability of default of a particular sovereign given the default of the sovereign system excluding that sovereign. This process will reveal the resilience of each sovereign to system-wide sovereign defaults. Figure 3 presents the results. During the sovereign debt crisis, we observe that peripheral sovereigns are the least resilient to the default of the sovereign system. From late 2011 to the end of our sample period, Greece, Italy, Portugal, and Spain, are guaranteed to default given the default of the sovereign system. In contrast, the resilience of Ireland improves dramatically as its conditional joint probability of default given the default of all other sovereigns decreases from 100% on November 2012 to 51% by the end of our sample period. The weak resilience of peripheral countries during the sovereign debt crisis is most likely a result of their dependence on other EA states for bailout funds. Therefore, if negative events occur in the rest of the sovereign system, serious repercussions would follow for the peripheral sovereigns. On the other end of the spectrum, Germany and the Netherlands are highly resilient to systemic default risk, reinforcing the pivotal role that these two sovereigns play in maintaining the stability of the EA. We also observe that Sweden and Norway are two of the sovereigns most resilient to systemic default risk. This is expected because neither sovereign is part of the EA and investors perceived the government bond markets of both sovereigns to be safe havens during the sovereign debt crisis.

4.2. The Systemic Impact of Peripheral Sovereigns

In the preceding section, we show that the peripheral sovereigns were the least resilient to systemic default risk. Recent literature provides evidence that peripheral sovereigns are the main source of instability in the EA (see, e.g., Aizenman, Hutchison, & Jinjarak, 2013; Arghyrou & Kontonikas, 2012; Beirne & Fratzscher, 2013; Black et al., 2013; De Santis, 2012; Gorea & Radev, 2014). Given the potential contagion between peripheral sovereigns and the healthy core, we turn our attention to two special dimensions: the systemic risk within the peripheral sovereigns and potential cascade effects between the peripheral and the core.[10]

Within the peripheral sovereign system, we are especially concerned with the transmission of systemic risk between the smaller sovereigns (Greece, Ireland, and Portugal) and the larger economies (Italy and Spain). Figure 4 presents the conditional joint probability of default of each peripheral sovereign given the default of other peripherals. There are strong systemic spillover effects between Greece, Ireland, and Portugal. For example, the *CoJPoD* value of Greece given the joint default of Ireland and Portugal reached 77% towards the end of our sample period, which is even larger than its *CoJPoD* given the joint default of Italy and Spain. Similarly, the *CoJPoD* value of Portugal given the joint default of Greece and Ireland reached 62% by September 2013. Consistent with Ireland's economic recovery, the *CoJPoD* value of Ireland given the joint default of Greece and Portugal remained relatively stable around 20% for the majority of 2013. Another observation is the importance of the larger peripheral sovereigns in maintaining the stability of the

[10]Cascade effects refer to the degree of systemic impact on the sovereign system given the default of different *combinations* of peripheral sovereigns.

peripheral sovereign system. For instance, for much of the sovereign debt crisis, the magnitude of *CoJPoD* for Ireland and Portugal given the joint default of Italy and Spain is much larger than that given the joint default of all peripheral sovereigns. Specifically, the *CoJPoD* values of Ireland and Portugal given the joint default of Italy and Spain reached maximum values of 66% and 68%, respectively, on July 2011.

Another important theme in ongoing debates is whether a default in the smaller peripheral sovereigns could migrate into Italy and Spain. On May 2010, the European Financial Stability Facility (EFSF) was established to provide financial assistance to EA member states experiencing financing difficulties. The facility had a lending capacity of 440 billion euros that could be combined with loans up to 250 billion euros from the International Monetary Fund (IMF). As of December 2013, Eurostat data reported the public debt of Ireland and Portugal to be 203 billion euros and 214 billion euros, respectively. Therefore, the financial distress of smaller peripheral sovereigns can be dissolved by financial stabilization mechanisms. In contrast, the combined public debt of Italy and Spain far exceeded the lending capabilities of the EFSF. Therefore, we focus specifically on the ITA and SPA panels in Fig. 4. It can be seen that the *CoJPoD* value of Italy given the default of Spain is consistently higher than that given the joint default of Greece, Ireland, Portugal, and Spain. Similarly, the *CoJPoD* of Spain given the default of Italy is also consistently greater than that given the joint default of Greece, Ireland, Portugal, and Italy. At first glance, such an observation might seem counterintuitive: How is it that the *CoJPoD* of Italy/Spain is lower given the default of four other sovereigns compared to when given the default of a single sovereign? This result can be explained after closer examination of the correlation structure of the sovereign system in Table 2. Specifically, the correlation between Italy and Spain is 0.85, whereas the average correlation between Italy and Greece, Ireland, Portugal, and Spain is much lower, at 0.53. As explained in Section 2, *CoJPoD* is constructed on the basis of interconnection; thus, the default of a highly interconnected sovereign (Italy/Spain) will cause a greater increase in *CoJPoD*. We also observe very similar time variation in the *CoJPoD* of Italy given the joint default of Ireland and Portugal compared to when given the default of all peripheral sovereigns. The same observation goes for Spain. This result suggests that the transmission of systemic risk to Italy and Spain due to negative shocks in Ireland and Portugal is just as potent as negative shocks to the entire peripheral sovereign system.

We now investigate potential cascade effects between the peripheral sovereigns and the rest of the sovereign system. Figure 5 presents the conditional joint probability of default of the rest of the sovereign system given the default of one, two, three, four, or all five peripheral sovereigns. The most immediate observation is that there is a large amount of core–peripheral divergence, in the sense that different combinations of peripheral sovereign defaults have varying degrees of systemic impact on the rest of the sovereign system. The first panel shows that the standalone defaults of Italy and Spain cause the most instability to the sovereign system, with *CoJPoD* reaching maximum values of 30% and 32%, respectively, on December 2011. When two peripheral sovereigns jointly default (second panel), Italy and Spain are again the most systemically important. However, towards the end of the sample period, smaller peripheral sovereigns, such as Ireland and Portugal, are just as systemically important, indicating that the smaller peripheral sovereigns also have the potential to cause large cascade effects. The third and fourth panels show that the default of Ireland, Italy, and Spain and the default of Ireland, Italy, Portugal, and Spain, respectively, have the greatest destabilizing effects on the perceived default vulnerability of the sovereign system. The high level of heterogeneity in the degree of systemic impact when different peripheral sovereigns default implies that regulators should take into account not only the size of peripheral sovereign defaults but also which combinations of peripheral sovereigns default.

In summary, our results from Figs. 4 and 5 imply that the increased systemic relation between the peripheral and the core has two main components. First, a default within the peripheral sovereign system may serve as a precursor for subsequent peripheral sovereign defaults, that is, intra-peripheral contagion. Furthermore, the transmission of systemic risk within the peripheral sovereign system is bidirectional, that is, the default of large peripheral sovereigns causes systemic spillover to the small peripheral sovereigns but the default of small peripheral sovereigns could also have destabilizing effects on the large peripheral sovereigns. Second, increased conditional probabilities of default within the peripheral sovereign system signals an increased probability of future sovereign rescues, ultimately to be funded by the healthy core sovereigns. Therefore, peripheral sovereign defaults have the potential to cascade into the core sovereign system.

4.3. Systemic Risk in the European Banking System

We now shift our attention from a pure sovereign perspective and investigate the systemic risk of the European banking system. We attempt to uncover the most systemically important banks and quantify their contribution to the systemic risk of the European banking system. We first examine the systemic risk contributions of banks at the country level and then at the individual bank level. Figure 6 presents the conditional joint probability of default of the banking system given the joint default of all banks in the sovereign listed in the title of each panel. During the global financial crisis, French and German banks contributed the most to the systemic risk of the banking system. The *CoJPoD* value of the banking system given the default of French and German banks peaked at 25% and 23%, respectively. However, banks in the larger peripheral sovereigns, such as Italy and Spain, were not far behind in terms of systemic importance, as the *CoJPoD* of the banking system given the default of Italian and Spanish banks peaked at values of 19% and 21%, respectively. Consistent with the notion that the stability of the EA banking system also largely depends on the solvency of non-EA banks, we observe that the *CoJPoD* of the banking system given the default of UK and Swiss banks grew to 18% and 23%, respectively, during the midst of the global financial crisis. Interestingly, the *CoJPoD* of the banking system given the default of Portuguese banks peaked at 14% shortly after the Lehman Brothers' collapse in late 2008, which is almost identical to the *CoJPoD* given the default of Austrian and Belgian banks, both of which attained a maximum value of 13%. This observation highlights the systemic importance of banks in smaller peripheral sovereigns.

The systemic risk contributions of banks in some European sovereigns changed dramatically between the global financial crisis and the sovereign debt crisis. In particular, of the peripheral sovereigns, the *CoJPoD* given the default of Italian and Spanish banks increased the most during the sovereign debt crisis. The differences between the maximum *CoJPoD* values during the global financial crisis and in the sovereign debt crisis are 6% and 7% for Italian and Spanish banks, respectively. The increased importance of banks in these countries could be due to their local risk concentration and their increased holdings of sovereign debt. Within the core sovereigns, French banks continued to contribute the most to the systemic risk of the banking system. The *CoJPoD* of the banking system given the default of French banks attained a maximum of 34% on November 2011, which is almost 9% higher than the maximum *CoJPoD* value during the global financial crisis. In comparison, the systemic risk contribution of German banks decreased considerably during the sovereign debt crisis. Banks in Switzerland and the United Kingdom became major players in the sovereign debt crisis as the *CoJPoD* of the banking system given the default of UK and Swiss banks climbed to maximum values of 32% and 38%, respectively.

We now investigate the systemic risk contribution of banks at the individual bank level. Table 3 presents the conditional joint probability of default of the banking system given the default of individual banks on five dates: (i) 15 September 2008, the day Lehman Brothers filed for bankruptcy; (ii) 10 March 2009, the date of the highest *CoJPoD* values during the global financial crisis for the majority of panels in Fig. 6; (iii) 2 May 2010, when Greece accepted the 110 billion euro EU–IMF loan package; (iv) 25 November 2011, the date of the highest *CoJPoD* value during the sovereign debt crisis for the majority of panels in Fig. 6; and (v) 19 December 2013, the date of the lowest *CoJPoD* value at the end of our sample period for the majority of panels in Fig. 6. As a measure of bank size during the sovereign debt crisis, the last two columns present the total assets and total liabilities in 2011 of each bank in billions of euros.

The most immediate observation is that the biggest contributors to the systemic risk of the banking system often coincide with the biggest banks in the sovereign. For example, the *CoJPoD* of the banking system given the default of the biggest bank in Spain, Banco Santander SA, was 32.5% on 25 November 2011. This value is much larger than *CoJPoD* given the default of the smallest bank in Spain, Banco de Sabadell SA, which was only 19.5% on the same date. Interestingly, the systemic risk contribution of Banco Santander SA is almost identical in magnitude to that of Deutsche Bank AG, which attained a *CoJPoD* value of 32.2% on 25 November 2011. This result further reinforces the systemic importance of banks in peripheral sovereigns. Another observation is that while Fig. 6 shows that the *joint* default of French banks contributed the most to the systemic risk during the global financial crisis and the sovereign debt crisis, Table 3 shows that *individual* defaults of French banks are just as systemically relevant. For example, the *CoJPoD* of the banking system given the default of the largest French bank, BNP Paribas, was 29.3% and 33.3% on 10 March 2009 and 25 November 2011, respectively. These two *CoJPoD* values are significantly larger than almost all other *CoJPoD* values given the default of

EA banks on the same two dates. Our results suggest that bank size and interdependence are crucial factors in determining the systemic importance of individual banks, which is in line with Tarashev, Borio, and Tsatsaronis (2009). Further corroborating the systemic importance of non-EA banks, we see that the largest banks in the United Kingdom and Switzerland all maintained very high *CoJPoD* values throughout the sovereign debt crisis.

Overall, our results support the actions taken by regulators and policymakers during the sovereign debt crisis from several perspectives. First, regulators often allowed small banks to fail. Our results indicate that small banks are generally less systemically important to the banking system; hence such actions are justified. Second, the EU and IMF have worked hard to bail out too-big-to-fail banks instead of letting them fail. Our results support this course of action, since the default of large banks is associated with greater systemic ramifications. Finally, our results support the policy implications of handling too-big-to-fail banks by shrinking their size or breaking them up into smaller entities to make them less systemically risky.

4.4. Evolution of Systemic Risk in the Combined European Sovereign and Banking System

Up until now, our focus has been on the sovereign system and banking system in isolation. We now consider sovereigns and banks as entities of an entire system and examine the evolution of systemic risk in this multivariate system. We choose sovereigns to be the trigger of default and examine their systemic impact on the banking system. Figure 7 presents the conditional joint probability of default of the banking system given the default of the sovereign in the title of each panel. The *CoJPoD* of the banking system given the default of core sovereigns reached maximum values between 18% and 21% during the global financial crisis, while *CoJPoD* given the default of larger peripheral sovereigns such as Italy and Spain peaked at 17%. This result not only indicates that investors perceived the systemic impact of core sovereigns and the large peripheral sovereigns to be roughly the same, but also shows that the European banking system was prone to systemic shocks originating from the United States. The onset of the sovereign debt crisis saw the systemic risk rise dramatically. The *CoJPoD* of the banking system given the default of Germany reached historical highs of 32% in late 2011. The systemic risk of Italy and Spain were not far behind, with *CoJPoD* values of 25% and 27%, respectively. Such high levels of bank default risk reflect the widespread panic and relentless unrest as European sovereigns adopted various austerity measures in an attempt to secure further bailout packages to ward off the pending catastrophe. For a closer examination of *CoJPoD*, we split its evolution into two periods. The first and second panels of Fig. 8 present the time-varying dynamics of *CoJPoD* during the global financial crisis and the sovereign debt crisis, respectively. We choose a core sovereign (Germany), a peripheral sovereign (Italy), and a non-EA sovereign (United Kingdom) to be the triggers of default.

The systemic risk was lowest at the beginning of our sample period (first panel of Fig. 8) but began to climb steadily as shocks from the United States echoed into the European banking sector. The first peak occurred on 14 March 2008, when the Federal Reserve and JP Morgan bailed out Bear Stearns. However, this episode was quickly defused due to rapid interventions by the Federal Reserve. A small peak materialized on 7 July 2008, when Fannie Mae and Freddie Mac plunged on capital concerns. Although these two enterprises played a key role in the US housing market, the European banking system seemed to be relatively unfazed. The first major systemic shock to the European banking system occurred on 15 September 2008, when Lehman Brothers filed for bankruptcy. The *CoJPoD* values of the banking system given the default of Germany, Italy, and the United Kingdom were 14%, 12%, and 11%, respectively. A period of recovery followed, as the G20 Summit vowed to boost growth and prevent future crises. However, this pledge was short-lived, as the *CoJPoD* given the default of Germany peaked at 21% on 10 March 2009, coinciding with the Dow Jones Industrial Average slumping to an all-time low. This result shows that the European banking system was adversely affected by the bearish nature of the US market at that time. Major contributing factors included the widespread lack of due diligence by market participants in the global financial markets and the advent of increasingly complex financial products that were used to mask excessive leverage that exploited vulnerabilities in the global financial system. Indeed, the significant rise in our *CoJPoD* measure shows that European banks were not spared the after-effects of such events. It was not until 2 April 2009, when the G20 set up the Financial Stability Board, that global financial markets began to calm down. This outcome was largely due to the adoption of policies intended to stimulate the economy, provide liquidity, enhance bank regulation, and reinforce international cooperation. Following such actions, the level of systemic risk began to decline, indicating a period of prolonged recovery.

The evolution of *CoJPoD* throughout the sovereign debt crisis was mostly a result of credit events spawned within the EA (second panel of Fig. 8) rather than external shocks from the United States. The *CoJPoD* value increased sharply on 2 May 2010, when Greece signed a loan package of 110 billion euros with the EU and IMF. The release of the 2010 round of banking stress tests on 23 July 2010 revealed that banks were likely to suffer losses on their sovereign debt exposures given a negative sovereign shock. Consistent with the stress test results, the *CoJPoD* of the banking system given a sovereign default maintained an upward trend. Positive news was released on 12 January 2011 related to the expansion of the lending facilities of the EFSF and on 19 February 2011, when the G20 decided to focus on global imbalances. The decrease in *CoJPoD* after these announcements indicates that the proposed course of action was successful in reducing the systemic risk. The release of the 2011 round of banking stress tests on 15 July 2011 marked a new period of heightened systemic risk in the EA. This round of stress test results revealed that banks in peripheral sovereigns were unlikely to weather negative sovereign shocks. The negative outlook was further reinforced at the G20 Summit on 14 October 2011, when concerns were raised regarding the possible financial contagion of a Greek default spreading to core sovereigns and accelerating the fiscal distress of peripheral sovereigns. The *CoJPoD* measure successfully captures this negative information as it reached an all-time high on 30 November 2011. A series of events followed that aimed to improve the liquidity of the banking system and prevent peripheral sovereign defaults. These policy implementations had a profound effect on our *CoJPoD* measure, signalling a period of continuous decline in systemic risk. To sum up, our findings indicate that major events during the global financial crisis and the European sovereign debt crisis strongly coincide with the inflection points in our *CoJPoD* measure.

4.5. Decomposition of Systemic Risk

As mentioned in Section 2.4, *CoJPoD* is a risk-neutral measure of systemic risk that incorporates information not only on physical default risk but also on risk premium components such as the liquidity risk premium, the default risk premium, and the sovereign risk premium. Our aim is to decompose the systemic risk of the combined sovereign and banking system and determine how much of its movement is induced by changes in the physical default loss of banks and how much is steered by changes in market sentiments (change in perceptions towards liquidity risk, default risk, and sovereign risk). To achieve this, we use the conditional joint probability of default of the sovereign system given the joint default of all banks within a particular sovereign as our measure of systemic risk. We choose banks to be the trigger of default because the DTD is a measure of physical default risk for banks only. Thus, by conditioning on the default of banks, we allow the systemic risk of the sovereign system to be influenced by the physical probabilities of default of banks.

In Fig. 9, the solid line of each panel is the conditional joint probability of default of the sovereign system given the joint default of all banks in the sovereign listed in the title of the panel. The values of the conditional joint probability of default are given on the left vertical axis in percent. The dotted line of each panel is the average DTD of all banks in the sovereign listed in the title of the panel. The values of the DTD are given on the right vertical axis.[11] The most immediate observation for all panels is that from the beginning of our sample to 10 March 2009 (the first major peak in the *CoJPoD* series during the global financial crisis), *CoJPoD* and the DTD are moving in opposite directions. Since a lower DTD means that a bank is closer to default, this negative relation between the two series implies that increases in the systemic risk of the sovereign system were mostly a result of the increased physical default risk of banks during the global financial crisis. Consistent with the improving market conditions during the post-global financial crisis recovery period to the beginning of the sovereign debt crisis, *CoJPoD* has a downward trend while the DTD has an upward trend. This result implies that the decrease in systemic risk can be attributed to the decreased probability of banks incurring actual losses.

Since the beginning of the sovereign debt crisis, *CoJPoD* and the DTD maintain a very strong negative relation in peripheral sovereigns such as Italy, Portugal, and Spain. In contrast, *CoJPoD* and the DTD share a positive relation in core sovereigns such as Austria, France, and Germany and in non-EA sovereigns such as Denmark, Sweden, Switzerland, and the United Kingdom. These results suggest that the physical stress placed on banks in peripheral sovereigns is the main contributor to the systemic risk of the sovereign system. Indeed, the sovereign debt crisis is a crisis of European origin; thus, the pure credit quality of banks in peripheral sovereigns is likely to be of much greater importance, given their

[11]The sample period is from 1 January 2008 to 1 July 2013 because DTD data are available only up to 1 July 2013.

large exposures to sovereign debt. Furthermore, deterioration of the real economy placed immense pressure on the European banking system, generating substantial downward revisions in the credit quality of banks in peripheral sovereigns. On the other hand, the physical condition of banks in non-peripheral sovereigns has been improving, as indicated by increasing values of DTD. Therefore, for banks in non-peripheral sovereigns, the systemic risk is primarily driven by risk premiums. The policy implications of this result is that, during a crisis, the sizes of bailout packages of market-based solutions tend to be considerably larger than is justified by an objective assessment of the default losses, because of changes in market sentiments.

We now take the analysis a step further and use regression analysis to examine the impact of physical default risk and risk premium components on the systemic risk of the sovereign system. The dependent variable in our panel regression is the conditional joint probability of default of the sovereign system given the joint default of all banks in a particular sovereign (denoted *CoJPoD* for short). We include three state variables to control for common risk factors. To control for market-wide credit risk, we include the European iTraxx index (*Itraxx*), which is an equally weighted index of the 125 most liquid CDS series in the European market. A higher iTraxx index value signals a higher overall credit risk in the economy; therefore, we expect a positive relation between the iTraxx index and *CoJPoD*. The second variable we include is the 24-month Vstoxx volatility index (*Vstoxx*). The Vstoxx index reflects the market perceptions of short-term volatility in Europe; therefore, increases in the Vstoxx index signify uncertainty regarding the strength of economic fundamentals of European sovereigns. We predict a positive relation between the Vstoxx index and *CoJPoD*. Lastly, we include the Europe Datastream Market Index (*Market*) to control for market-wide business climate. We predict that improving economic prospects, signalled by increases in the market index, should decrease *CoJPoD*. All three variables are obtained from Datastream. Our main variables include the liquidity risk premium (*LRP*), the default risk premium (*DRP*), the sovereign risk premium (*SRP*), and the DTD (*DTD*). The specification can thus be written as follows:

$$CoJPoD_{i,t} = \alpha + \beta \cdot Risk\ Premium_t + \gamma \cdot DTD_{i,t} + \phi \cdot X_t + \epsilon_{i,t} \qquad (5)$$

where $Risk\ Premium_t$ is the vector of risk premium variables, $DTD_{i,t}$ is the average

DTD of all banks in sovereign i, and X_t is the vector of control variables. In unreported tests, we find that most of our variables are non-stationary, which will yield spurious results when we run the regression in levels. To deal with this problem, we convert all variables into arithmetic returns. We run the regression using monthly observations from 1 January 2008 to 28 June 2013, since this is the frequency and period for which we have available DTD data.

Table 4 presents the results of the panel regression. Columns (1) to (3) include the risk premium variables individually, while column (4) includes the DTD individually. Column (5) uses all variables. Columns (6) and (7) use banks from peripheral and non-peripheral sovereigns, respectively. All columns employ sovereign fixed effects. We note that all three state variables have the expected signs and are significant across all columns. This result shows that the three state variables are successful in capturing sources of commonality and so we can be confident that the loadings on the risk premium variables and the DTD reflect the decomposition of systemic risk over and above what can be explained by fundamental factors. In columns (2) and (3), the coefficients of the default risk premium and the sovereign risk premium are both positive and highly significant, indicating that changes in market risk perceptions play an important role in driving the variation in the systemic risk of the sovereign system. Surprisingly, the coefficient of the liquidity risk premium is negative (column (1)), although marginally significant. The DTD has the expected negative coefficient (column (4)); however, its weak significance indicates that the effect of physical probabilities of default on the systemic risk of the full sample of sovereigns is not so clear-cut.

The multivariate joint regression in column (5) of Table 4 further reinforces the importance of risk premium components in driving up systemic risk as the coefficients of the default risk premium and sovereign risk premium continue to be positive and highly significant. Unexpectedly, the loading on the liquidity risk premium remains negative and actually increases in significance. One possible explanation for this result is the implementation of policies that were aimed at injecting liquidity into the banking system and relieving the financing troubles of European banks, for example, the Federal Reserve's dollar liquidity swap with the ECB in November 2011 and the ECB's long-term refinancing operations in December 2011. During the sovereign debt crisis, these interventions were not just a one-time occurrence; rather, market interventions became the new normal.

Thus, in this self-validating cycle of rescue packages, liquidity dry-ups could be a signal of market intervention that subsequently decreases the systemic risk. Finally, the DTD is still negatively related to the systemic risk of the sovereign system; however, it is only significant at the 10% level, suggesting that physical default risk has confounding effects on banks in peripheral and non-peripheral sovereigns. Consistent with the observation in Fig. 9, that the negative association between the DTD and the *CoJPoD* is stronger for banks in peripheral sovereigns, when we restrict our sample of banks to only those in the peripheral sovereigns, the coefficient of the DTD variable increases in significance while the sovereign risk premium decreases in significance (column (6)). This result supports the notion that physical probabilities of default play a larger role in determining the level of systemic risk for banks in peripheral sovereigns. In contrast, Fig. 9 also appears to suggest that it is mainly the risk premium components that induce increases in systemic risk for banks in non-peripheral sovereigns. We can confirm this observation, since column (7) shows that when we restrict our sample of banks to those in non-peripheral sovereigns, the DTD variable becomes insignificant while the sovereign risk premium increases in significance.

5. Conclusion

This paper uses the conditional joint probability of default to study the systemic risk of the European sovereign and banking system during the global financial crisis and the sovereign debt crisis. Although there is a significant amount of literature on sovereign and bank credit risk in isolation, there has been relatively little work in attempting to quantify the level of systemic risk between the two. This paper contributes to the topic by incorporating individual default risk characteristics combined with joint default risk dynamics to create a probabilistic measure of systemic risk that is applicable in a true multivariate setting. In addition, we fully exploit the conditional flexibility in the systemic risk measure by first investigating the level of systemic risk in the sovereign and banking system separately and then in the combined sovereign and banking system.

Our initial results are consistent with macroeconomic intuition. Specifically, we show that the conditional joint probability of default of the sovereign system given the default of core sovereigns, such as Germany and the Netherlands, is much higher than the conditional joint probability of default given the default of peripheral sovereigns, such as Italy and Spain. The advantage of our approach is that we are able to track the level of systemic risk in terms of probability. In particular, during the height of the sovereign debt crisis, the conditional joint probability of default of the sovereign system given the default of Germany reached a maximum of 47%, while the default of Italy and Spain only produced values of 30%. Interchanging the order of conditioning, we are able to reveal important information regarding the resilience of sovereigns to system-wide default. We show that all five peripheral sovereigns are the least resilient to sovereign system default, with the exception of Ireland, whose resilience improves dramatically towards the end of our sample period. Our results also confirm the importance of Germany and the Netherlands as core sovereigns in maintaining the stability of the EA.

Shifting our focus to the systemic impact of peripheral sovereigns, our results are in line with recent developments in the systemic risk literature. We show that the increased systemic activity between the peripheral sovereigns and the healthy core can be broken down into two components. First, we point out the large degree of systemic risk spillover within the peripheral sovereign system. Our results indicate that intra-peripheral systemic risk is bidirectional, that is, the default of larger peripheral sovereigns such as Italy and Spain poses severe systemic consequences for the smaller peripheral sovereigns such as Ireland and Portugal. However, negative shocks to small peripheral sovereigns can also cause a systemic collapse of large peripheral sovereigns. The second component is the potential for systemic risk to cascade from peripheral sovereigns to core sovereigns. In particular, we document great heterogeneity in the degree of systemic impact when different combinations of peripheral sovereigns default. Policy-wise, these results highlight the need to decrease the interdependence between the peripheral and the core during crisis periods. Furthermore, given the occurrence of peripheral sovereign defaults, regulators should take into account not only the size of the default, but also which combination of sovereigns defaulted.

Applying our measure of systemic risk in the European banking system unveils some notable results. We show that, of the EA banks, French banks contributed the most to the systemic risk of the banking system during both the global financial crisis and the sovereign debt crisis. However, banks in the larger peripheral sovereigns, such as Italy and Spain were not far behind in terms of systemic importance. In fact, the systemic risk contributions of these banks increased the most during the sovereign debt crisis. Our results also indicate that the stability of the banking system is largely attributable to the solvency of non-EA banks in the United Kingdom and Switzerland. Indeed, during the sovereign debt crisis, banks in these sovereigns would have been the highest contributors to the systemic risk of the banking system had they defaulted. Examining systemic risk at the individual bank level reveals that the biggest contributors to the systemic risk of the banking system often coincide with the biggest banks in the sovereign. Thus, our results lend support to the course of action taken by regulators and policymakers during the sovereign debt crisis in dealing with too-big-to-fail banks and preventing their failure.

Merging the sovereign and banking system into one multivariate system and using sovereigns as the trigger of default, we show that the evolution of the conditional joint probability of default of the banking system coincides with major events throughout our sample period. Although systemic risk was generally quite tame during the global financial crisis, it peaked shortly after the Lehman Brothers' collapse as the conditional joint probability of default of the banking system given the default of core sovereigns reached values of around 21%. However, the onset of the sovereign debt crisis saw systemic risk increase to unprecedented levels, with the conditional joint probability of default given the default of Germany reaching historical highs of 32%. To determine the driving forces of systemic risk, we condition on the default of banks and examine the decomposition of the systemic risk of the sovereign system. Our results indicate that the default risk premium and the sovereign risk premium played a major role in driving the variation in systemic risk. In addition, we show that the physical probability of default is also a significant component of systemic risk, especially for banks in peripheral sovereigns.

A. Proofs

A.1. Framework for the Consistent Information Multivariate Density Optimization (CIMDO) Methodology

Assume there are n entities in the system where $X_1, X_2, \cdots, X_n$ denote the random variables corresponding to the natural logarithm of assets of institution $I_1, I_2, \cdots, I_n$, respectively. Define the Knullback-Leibler objective function as:

$$C(p,q) = \int\int\cdots\int p(x_1,x_2,\cdots,x_n)\ln\left[\frac{p(x_1,x_2,\cdots,x_n)}{q(x_1,x_2,\cdots,x_n)}\right]dx_1\cdots dx_{n-1}dx_n \tag{A.1}$$

where $q(x_1, x_2, \cdots, x_n) \in \mathbb{R}^n$ is the prior distribution and $p(x_1, x_2, \cdots, x_n) \in \mathbb{R}^n$ is the posterior distribution.

We minimize the functional in Eq. (A.1) with respect to p subject to the following moment consistency constraints:[12]

$$\begin{aligned}
\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\chi_{[X_d^{I_1},\infty)}dx_1\cdots dx_{n-1}dx_n &= PoD_{I_1}\\
\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\chi_{[X_d^{I_2},\infty)}dx_1\cdots dx_{n-1}dx_n &= PoD_{I_2}\\
&\vdots\\
\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\chi_{[X_d^{I_n},\infty)}dx_1\cdots dx_{n-1}dx_n &= PoD_{I_n}\\
\int\int\cdots\int p(x_1,x_2,\cdots,x_n)dx_1\cdots dx_{n-1}dx_n &= 1
\end{aligned}$$

where $PoD_{I_1}, PoD_{I_2}, \cdots, PoD_{I_n}$ correspond to the bootstrapped probabilities of default of institution $I_1, I_2, \cdots, I_n$, respectively. For $i = 1, 2, \cdots, n$, define $\chi_{[X_d^{I_i},\infty)}$ as:

$$\chi_{[X_d^{I_i},\infty)} = \begin{cases} 1 & \text{if } X_i \geq X_d^{I_i} \\ 0 & \text{if } X_i < X_d^{I_i} \end{cases}$$

[12] Note that we do not include the positivity constraint, $p(x_1, x_2, \cdots, x_n) \geq 0$, since we explicitly assume the prior is a non-negative function.

The corresponding Lagrangian is defined as:

$$
\begin{aligned}
L(p,q) = &\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\ln(p(x_1,x_2,\cdots,x_n))dx_1\cdots dx_{n-1}dx_n \\
&-\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\ln(q(x_1,x_2,\cdots,x_n))dx_1\cdots dx_{n-1}dx_n \\
&+\lambda_1\left[\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\chi_{[X_d^{I_1},\infty)}dx_1\cdots dx_{n-1}dx_n - PoD_{I_1}\right] \\
&+\lambda_2\left[\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\chi_{[X_d^{I_2},\infty)}dx_1\cdots dx_{n-1}dx_n - PoD_{I_2}\right] \\
&+\cdots \\
&+\lambda_n\left[\int\int\cdots\int p(x_1,x_2,\cdots,x_n)\chi_{[X_d^{I_n},\infty)}dx_1\cdots dx_{n-1}dx_n - PoD_{I_n}\right] \\
&+\mu\left[\int\int\cdots\int p(x_1,x_2,\cdots,x_n)dx_1\cdots dx_{n-1}dx_n - 1\right]
\end{aligned}
$$

where λ_i for $i = 1, 2, \cdots, n$ denotes the Lagrange multipliers for the n moment consistency constraints and μ is the Lagrange multiplier for the unity constraint.

The optimal solution to the multivariate CIMDO posterior distribution is given by:

$$
p(x_1,\widehat{x_2,\cdots},x_n) = q(x_1,x_2,\cdots,x_n)\exp\left\{-\left[1+\widehat{\mu}+\sum_{i=1}^{n}\widehat{\lambda}_i\chi_{[X_d^{I_i},\infty)}\right]\right\} \tag{A.2}
$$

where $\widehat{\lambda_1}, \widehat{\lambda_2}, \cdots, \widehat{\mu}$ denote the consistent estimators of $\lambda_1, \lambda_2, \cdots, \mu$, respectively.

A.2. The GCE Method

In order to dynamically update the posterior distribution, we need to solve for the Lagrange multipliers in Eq. (A.2) on a daily basis. We provide a solution to solve for consistent estimators of the Lagrange multipliers by using the GCE method. Under the cross-entropy postulate, we minimize the Csiszár measure of cross-entropy between the prior q and the posterior p as follows:

$$\min_{p\in\mathbb{P}} D(p \to q) = \int_{\boldsymbol{\zeta}} q(\mathbf{x})\psi\left(\frac{p(\mathbf{x})}{q(\mathbf{x})}\right) d\mathbf{x} \tag{A.3}$$

where $\mathbf{x} = [x_1, x_2, \cdots, x_n]^T \in \boldsymbol{\zeta} \subset \mathbb{R}^n$ and $\mathbb{P} = \left\{p : \int p(\mathbf{x})d\mathbf{x} = 1, p(\mathbf{x}) \geq 0,\ \forall\ x \in \boldsymbol{\zeta}\right\}$. Additionally, ψ is a function that satisfies:

1. $\psi : \mathbb{R}^+ \to \mathbb{R}$ is a continuous twice-differentiable function.
2. $\psi(1) = 0$
3. $\psi''(x) > 0\ \forall\ x \in \mathbb{R}^+$. This is called the convexity assumption.

The minimization in Eq. (A.3) is subject to the generalized moment constraint set, Ω:

$$\mathbb{E}_p[K_i(\mathbf{X})] = \int_{\boldsymbol{\zeta}} p(\mathbf{x})K_i(\mathbf{x})d\mathbf{x} = \widehat{\kappa}_i,\ \text{for } i = 1, 2, \cdots, n \tag{A.4}$$

where K_i is a set of suitably chosen functions and $\widehat{\kappa}_i$ is some estimated quantity that describes the behaviour of the system.

The convexity assumption on ψ allows us to invoke the theory of duality and in particular, the Strong Duality Theorem (see, e.g., Borwein & Lewis, 1991; Decarreau, Hilhorst, Lemarechal, & Navaza, 1992). We define the Primal Problem to be:

$$\begin{aligned} &\min_p\ D(p \to q) \\ \text{subject to :}\ &\int p(\mathbf{x})K_i(\mathbf{x})d\mathbf{x} = \widehat{\kappa}_i,\ i = 1, 2, \cdots, n \\ &\int p(\mathbf{x})d\mathbf{x} = 1 \end{aligned}$$

The corresponding Lagrangian is given by:

$$L(p:\boldsymbol{\lambda},\lambda_0)=\int\left[q(\mathbf{x})\psi\left(\frac{p(\mathbf{x})}{q(\mathbf{x})}\right)-p(\mathbf{x})\underbrace{\sum_{i=0}^{n}\lambda_i K_i(\mathbf{x})}_{\text{Define } K_0(\cdot)=1}\right]d\mathbf{x}+\underbrace{\sum_{i=0}^{n}\lambda_i\widehat{\kappa_i}}_{\text{Define } \widehat{\kappa_0}=1} \tag{A.5}$$

where $\boldsymbol{\lambda}=[\lambda_1,\lambda_2,\cdots,\lambda_n]^T$ and λ_0 denotes the set of positive Lagrange multipliers for Ω. Under the Strong Duality Theorem, we have the following equivalence:

$$\underbrace{\min_{p\in\mathbb{P}}\{D(p\to q)\}}_{\text{Primal Problem}}=\underbrace{\max_{\boldsymbol{\lambda},\lambda_0}\left\{\inf_{p\in\mathbb{P}}L(p:\boldsymbol{\lambda},\lambda_0)\right\}}_{\text{Dual Problem}} \tag{A.6}$$

The equivalent Dual Problem is given by:

$$\begin{gathered}\max_{\boldsymbol{\lambda},\lambda_0}\left\{\inf_{p\in\mathbb{P}}L(p:\boldsymbol{\lambda},\lambda_0)\right\}\\ \text{subject to}:\;\;\boldsymbol{\lambda}\geq 0\end{gathered} \tag{A.7}$$

Under the convexity assumption, the function $\psi'(x)$ has a unique inverse over the positive reals. Thus,

$$p(\mathbf{x})=q(\mathbf{x})\psi'^{-1}\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{x})\right) \tag{A.8}$$

Substituting Eq. (A.8) into Eq. (A.5) yields:

$$\begin{aligned}L^*(\boldsymbol{\lambda},\lambda_0)&=\inf_{p\in\mathbb{P}}L(p:\boldsymbol{\lambda},\lambda_0)\\ &=\mathbb{E}_q\left[\psi\left(\psi'^{-1}\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{X})\right)\right)\right]-\sum_{j=0}^{n}\left\{\lambda_j\mathbb{E}_q\left[K_j(\mathbf{X})\psi'^{-1}\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{X})\right)\right]\right\}+\sum_{i=0}^{n}\lambda_i\widehat{\kappa_i}\end{aligned}$$

Define $\Psi'(x)=\psi'^{-1}(x)$, the simplest form of the Dual Problem is:

$$\max_{\boldsymbol{\lambda},\lambda_0}\;L^*(\boldsymbol{\lambda},\lambda_0)=\sum_{i=0}^{n}\lambda_i\widehat{\kappa_i}-\mathbb{E}_q\left[\Psi\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{X})\right)\right] \tag{A.9}$$

The Gradient of L^* with respect to λ_j is defined as:

$$\frac{\partial L^*}{\partial \lambda_j} = -\mathbb{E}_q\left[K_j(\mathbf{X})\Psi'\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{X})\right)\right] + \widehat{\kappa_j} \text{ for } j = 0, 1, \cdots, n \tag{A.10}$$

Consistent estimators for $\boldsymbol{\lambda}, \lambda_0$ can be obtained by solving $\nabla_{\boldsymbol{\lambda},\lambda_0} L^* = 0$:

$$\mathbb{E}_q\left[\Psi'\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{X})\right)\right] = 1 \tag{A.11}$$

$$\mathbb{E}_q\left[K_1(\mathbf{X})\Psi'\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{X})\right)\right] = \widehat{\kappa_1} \tag{A.12}$$

$$\vdots$$

$$\mathbb{E}_q\left[K_n(\mathbf{X})\Psi'\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{X})\right)\right] = \widehat{\kappa_n} \tag{A.13}$$

In general, we can rarely calculate the expectations in the above system of equations analytically, thus in practice, we numerically solve their stochastic counterparts:

$$\frac{1}{n}\sum_{k=1}^{n}\left[K_j(\mathbf{x}_k)\Psi'\left(\sum_{i=0}^{n}\lambda_i K_i(\mathbf{x}_k)\right)\right] = \widehat{\kappa_j} \text{ where } \{\mathbf{X}_k\}_{k=1}^{n} \sim q \text{ and } j = 0, 1, \cdots, n \tag{A.14}$$

The solution to this set of equations provides a set of consistent estimators for the Lagrange multipliers $\widehat{\boldsymbol{\lambda}} = [\widehat{\lambda_1}, \widehat{\lambda_2}, \cdots, \widehat{\lambda_n}]^T$ and $\widehat{\lambda_0}$.

To apply the GCE in the CIMDO framework, first define $\psi(x) = x\ln(x)$ as the Knullback-Leibler divergence, so that:

1. $\psi'(x) = \ln(x) + 1$
2. $\psi^{'-1}(x) = \Psi'(x) = \Psi(x) = \exp(x-1)$

Under this measure, the Csiszár cross-entropy distance is defined as:

$$D(p \to q) = \int_{\zeta} q(\mathbf{x}) \ln\left(\frac{p(\mathbf{x})}{q(\mathbf{x})}\right) d\mathbf{x}$$

where $\mathbf{x} \in \zeta \subset \mathbb{R}^n$, $p(\mathbf{x}) \in \mathbb{R}^n$ is the posterior distribution and $q(\mathbf{x}) \in \mathbb{R}^n$ is the prior distribution.

Our constraint set Ω is the set $\mathbb{E}_p\left[K_i(\mathbf{X})\right] = \widehat{\kappa_i}$ for $i = 0, 1, \cdots, n$ where $\widehat{\kappa_0} = 1$ and $K_0(\cdot) = 1$. We define $\{K_i(\mathbf{x})\}_{i=0}^n = \{\chi_i(\mathbf{x})\}_{i=0}^n$ where $\chi_i(\mathbf{x})$ is an indicator function which takes on the value of unity if x_i satisfies some condition and zero otherwise. Therefore, our constraint set becomes:

$$\mathbb{E}_p\left[\chi_i(\mathbf{X})\right] = \widehat{\kappa_i} \text{ for } i = 0, 1, \cdots, n \tag{A.15}$$

The Primal Problem is defined as:

$$\min_p D(p \to q) = \int_\zeta q(\mathbf{x}) \ln\left(\frac{p(\mathbf{x})}{q(\mathbf{x})}\right) d\mathbf{x}$$
$$\text{subject to } \mathbb{E}_p\left[\chi_i(\mathbf{X})\right] = \widehat{\kappa_i} \text{ for } i = 0, 1, \cdots, n$$

The solution to the Primal Problem using Eq. (A.8) is given by:

$$p(\mathbf{x}) = q(\mathbf{x}) \exp\left[\sum_{i=0}^n \lambda_i \chi_i(\mathbf{x}) - 1\right] \tag{A.16}$$

To see the equivalence between Eq. (A.16) and the CIMDO posterior distribution given by Eq. (A.2), define the Lagrange multipliers to be inherently negative and denote λ_0 as μ, this yields the following equivalent expression:

$$\widehat{p(\mathbf{x})} = q(\mathbf{x}) \exp\left\{-\left[1 + \widehat{\mu} + \sum_{i=1}^n \widehat{\lambda}_i \chi_i(\mathbf{x})\right]\right\} \tag{A.17}$$

We use Eq. (A.9) to solve for the Lagrange multipliers:

$$\max_{\boldsymbol{\lambda}, \lambda_0} \left\{\sum_{i=0}^n \lambda_i PoD_{I_i} - \mathbb{E}_q\left[\exp\left(\sum_{i=0}^n \lambda_i \chi_i\left(\mathbf{X}\right) - 1\right)\right]\right\} \tag{A.18}$$

where $PoD_{I_0} = 1$ and $\chi_0\left(\cdot\right) = 1$.

To maximize Eq. (A.18), we solve the following system of equations:

$$\mathbb{E}_q\left[\exp\left(\sum_{i=0}^{n}\lambda_i\chi_i\left(\mathbf{X}\right)-1\right)\right]=1 \tag{A.19}$$

$$\mathbb{E}_q\left[\chi_1\left(\mathbf{X}\right)\exp\left(\sum_{i=0}^{n}\lambda_i\chi_i\left(\mathbf{X}\right)-1\right)\right]=PoD_{I_1} \tag{A.20}$$

$$\vdots$$

$$\mathbb{E}_q\left[\chi_n\left(\mathbf{X}\right)\exp\left(\sum_{i=0}^{n}\lambda_i\chi_i\left(\mathbf{X}\right)-1\right)\right]=PoD_{I_n} \tag{A.21}$$

We numerically solve the above system of equations using Eq. (A.14) thereby obtaining a set of consistent estimators for the Lagrange multipliers $\widehat{\mu}, \widehat{\lambda_1}, \cdots, \widehat{\lambda_n}$.

B. Figures

Figure 1: **Sovereign probabilities of default and joint probability of default of the sovereign system**

Each panel (with the exception of the last one) presents the five-year annualized bootstrapped probabilities of default for each of the 14 sovereigns listed in Table 1. USD-denominated CDS spreads of maturities one to five years are used to derive the probabilities of default. The last panel (titled JPoD) presents the joint probability of default of the sovereign system. The correlation matrix used to construct the joint probability of default is given in Table 2. The sample period for all panels is from 1 January 2008 to 31 December 2013. The unit of measurement for the vertical axis is %.

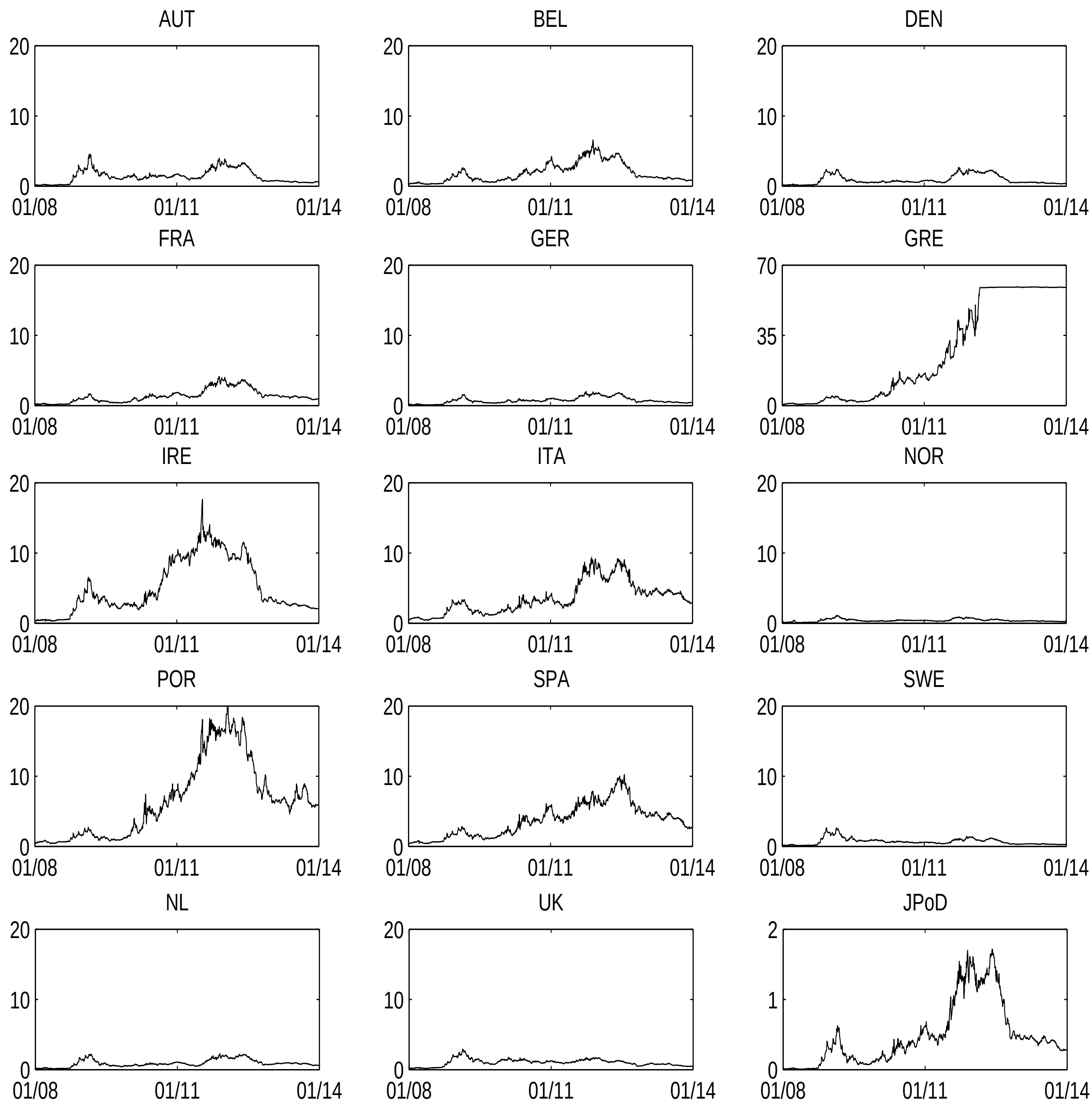


Figure 2: **Conditional joint probability of default of the sovereign system, given the default of a particular sovereign**

Each panel presents the conditional joint probability of default of the sovereign system, given the default of each of the 14 sovereigns listed in Table 1. The title of each panel is the sovereign that defaults. The correlation matrix used to construct the conditional joint probability of default is given in Table 2. The sample period for all panels is from 1 January 2008 to 31 December 2013. The unit of measurement for the vertical axis is %.

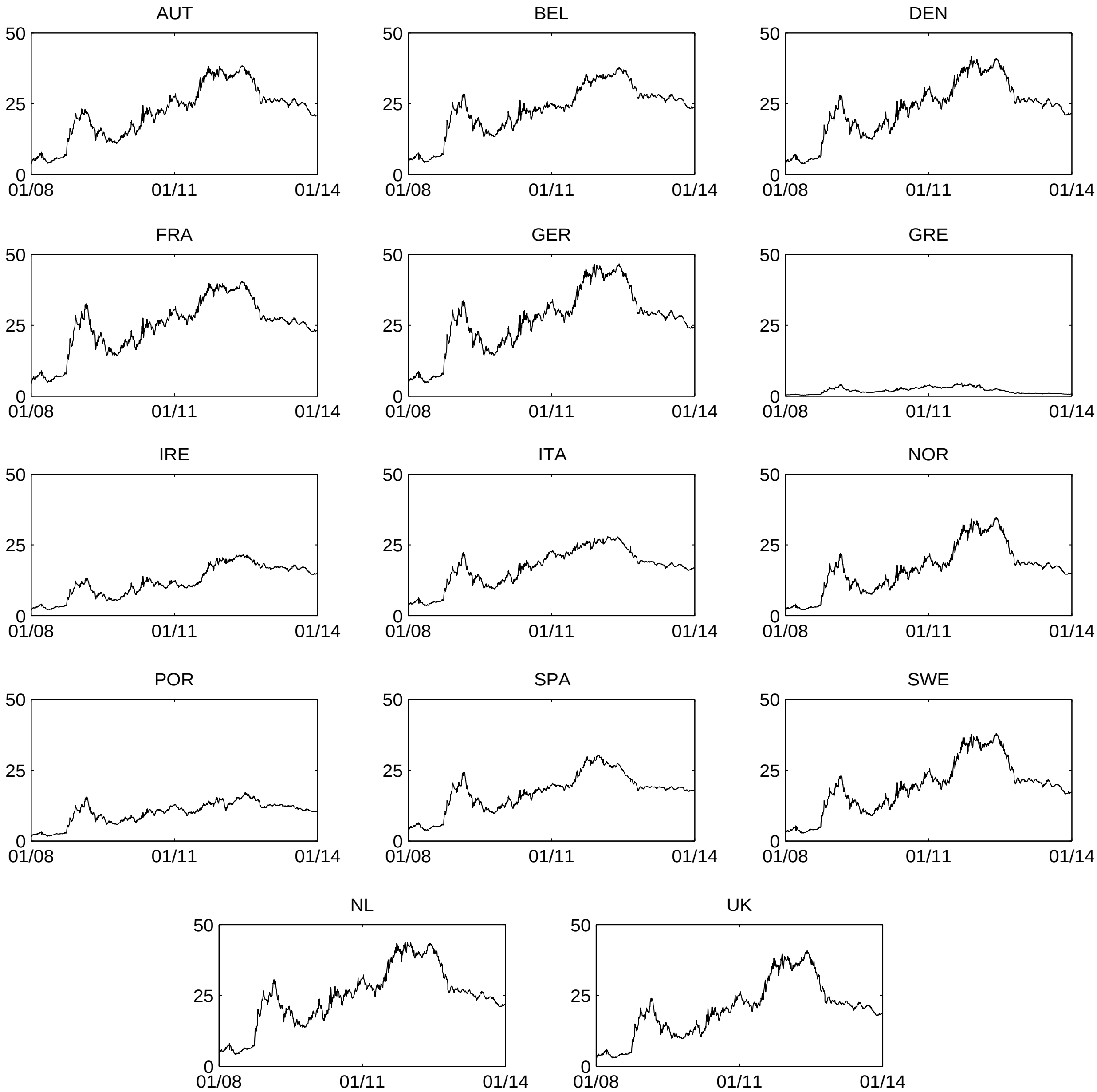


Figure 3: **Conditional joint probability of default of a particular sovereign, given the default of the sovereign system excluding that sovereign**

Each panel presents the conditional joint probability of default of each of the 14 sovereigns listed in Table 1, given the default of the sovereign system excluding the sovereign in the title of the panel. The correlation matrix used to construct the conditional joint probability of default is given in Table 2. The sample period for all panels is from 1 January 2008 to 31 December 2013. The unit of measurement for the vertical axis is %.

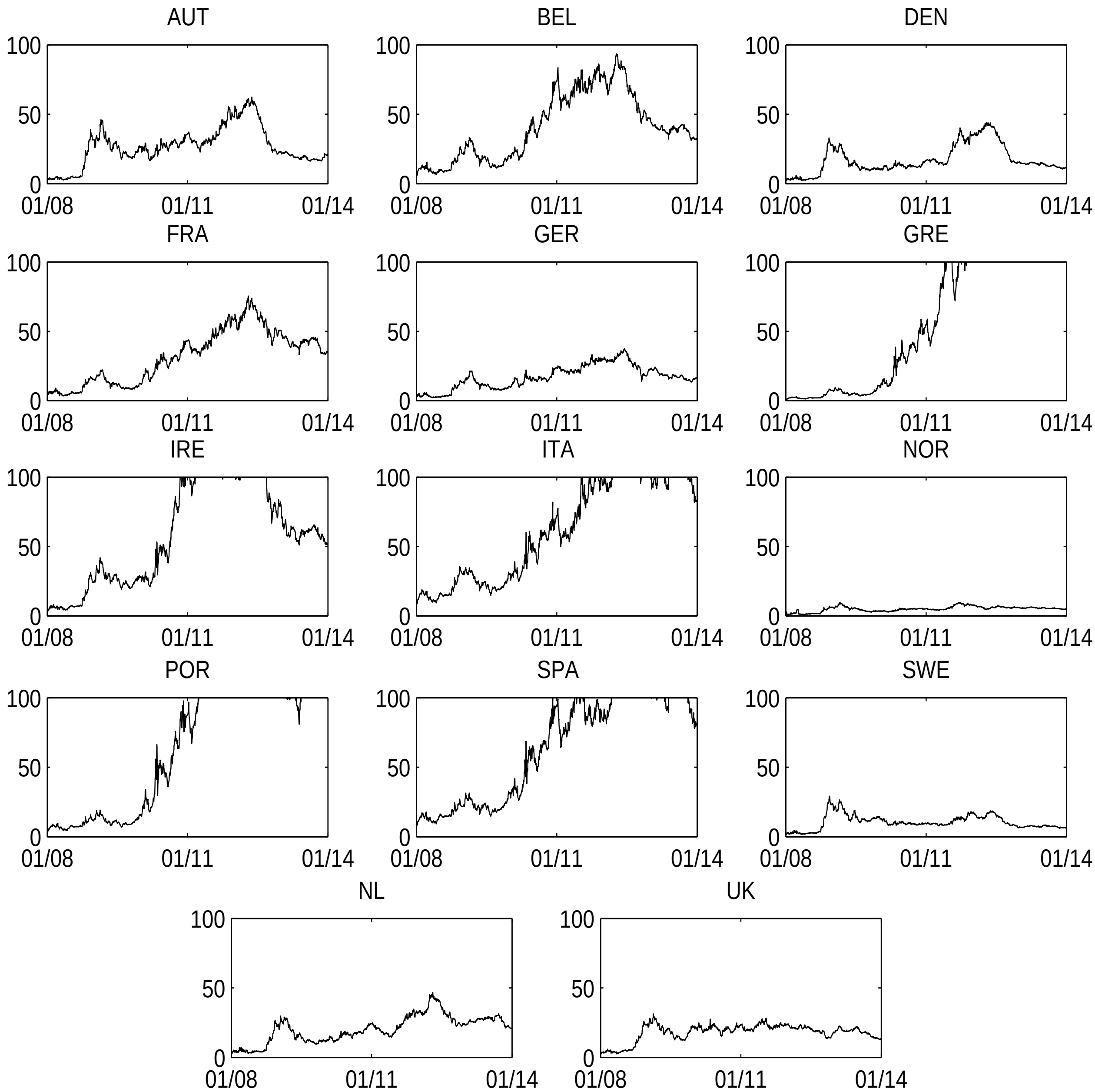


Figure 4: **Conditional joint probability of default of a particular peripheral sovereign, given the default of other peripheral sovereigns**

Each panel presents the conditional joint probability of default of each of the five peripheral sovereigns (Greece, Ireland, Italy, Portugal, and Spain), given the default of the sovereigns listed in the legend. The correlation matrix used to construct the conditional joint probability of default is given in Table 2. The sample period for all panels is from 1 January 2008 to 31 December 2013. The unit of measurement for the vertical axis is %.

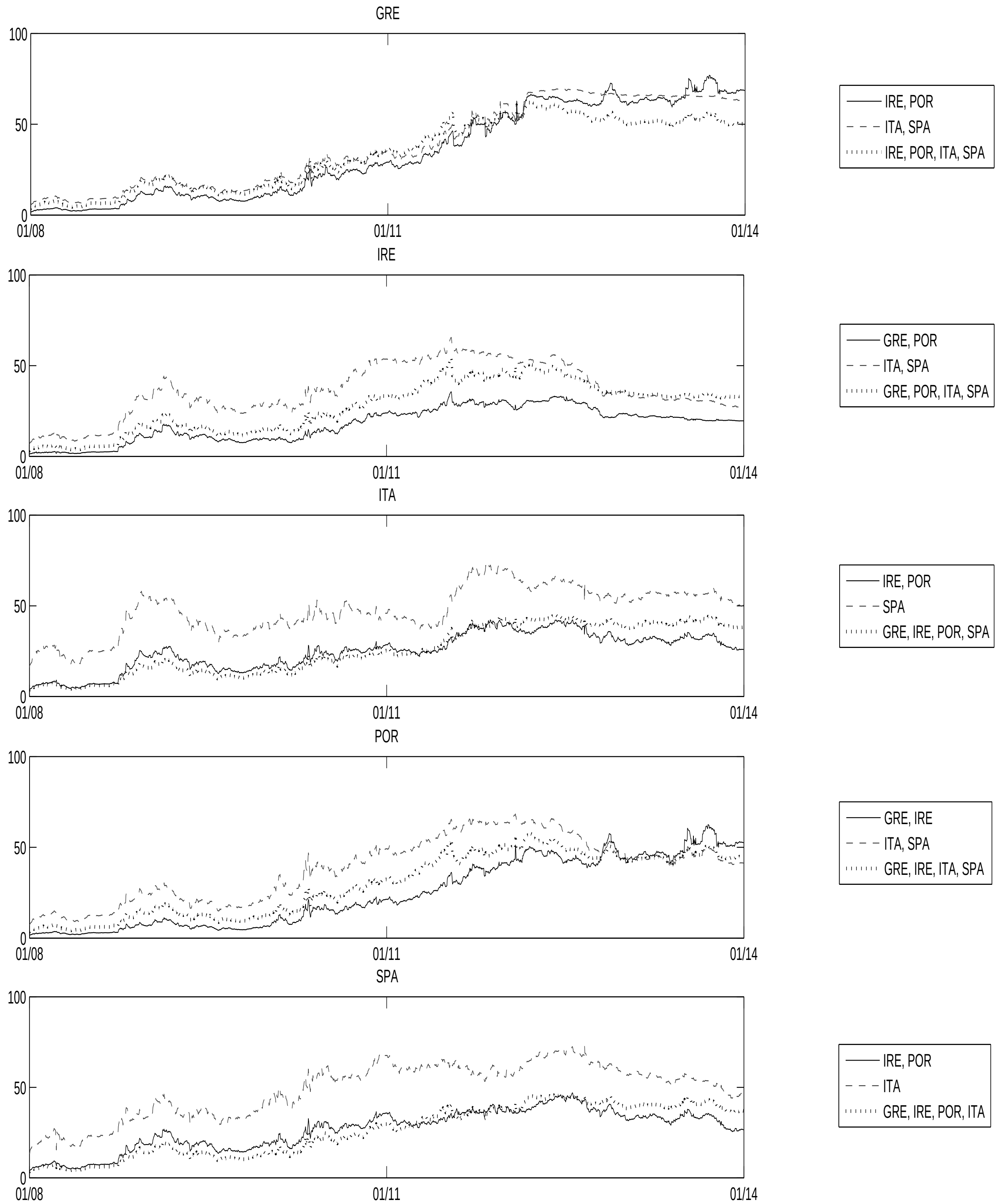


Figure 5: **Conditional joint probability of default of the sovereign system, given the default of peripheral sovereigns**

Each panel presents the conditional joint probability of default of the remaining sovereigns in the sovereign system, given the default of the peripheral sovereigns listed in the legend. The correlation matrix used to construct the conditional joint probability of default is given in Table 2. The sample period for all panels is from 1 January 2008 to 31 December 2013. The unit of measurement for the vertical axis is %.

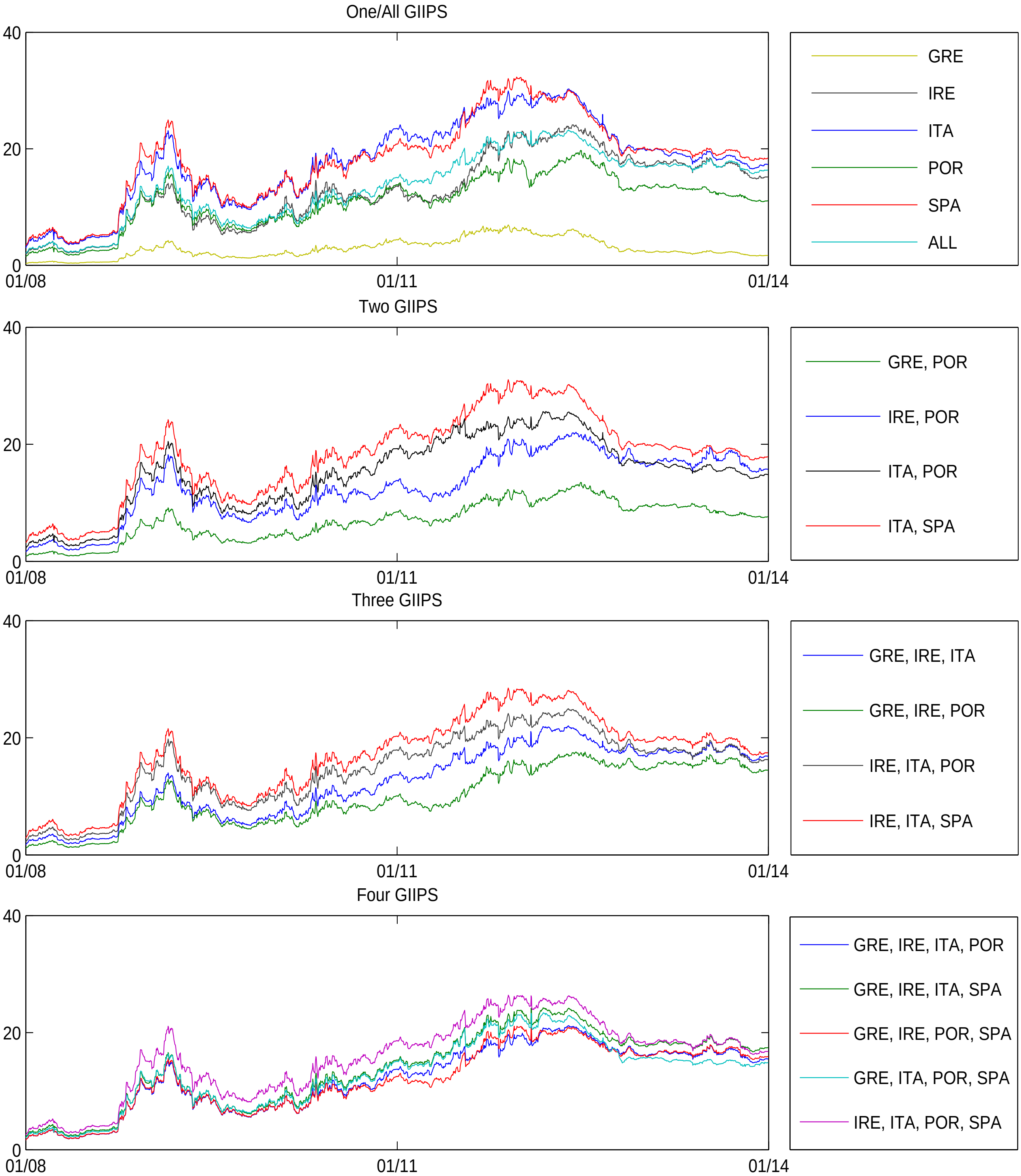


Figure 6: **Conditional joint probability of default of the banking system, given the joint default of all banks in a particular sovereign**
Each panel presents the conditional joint probability of default of the banking system, given the joint default of all banks in the sovereign listed in the title of the panel. The banks and their home country are listed in Table 1. The sample period for all panels is from 1 January 2008 to 31 December 2013. The unit of measurement for the vertical axis is %.

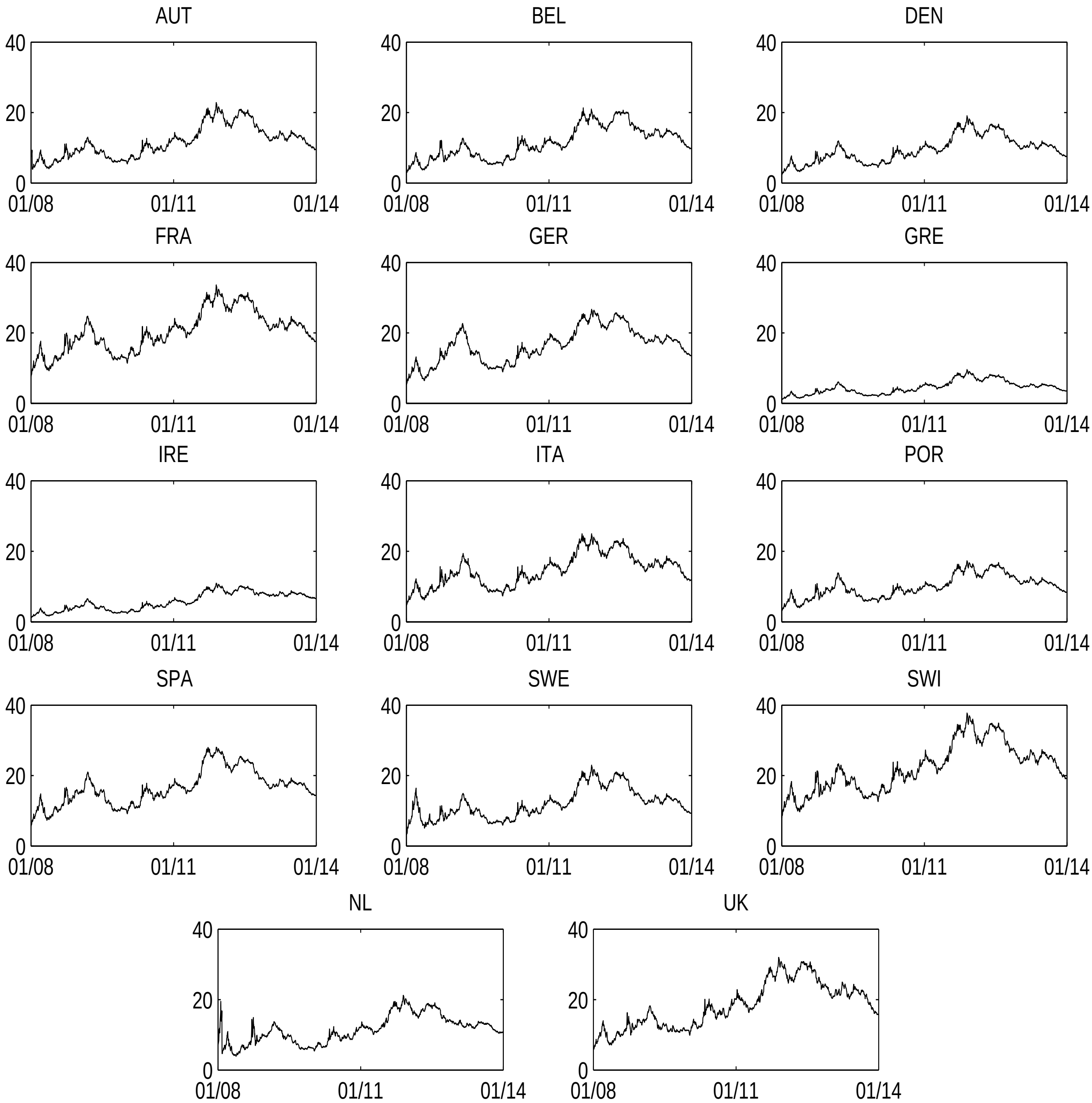


Figure 7: **Conditional joint probability of default of the banking system, given the default of a particular sovereign**

Each panel presents the conditional joint probability of default of the banking system, given the default of each of the 14 sovereigns listed in Table 1. The title of each panel is the sovereign that defaults. The sample period for all panels is from 1 January 2008 to 31 December 2013. The unit of measurement for the vertical axis is %.

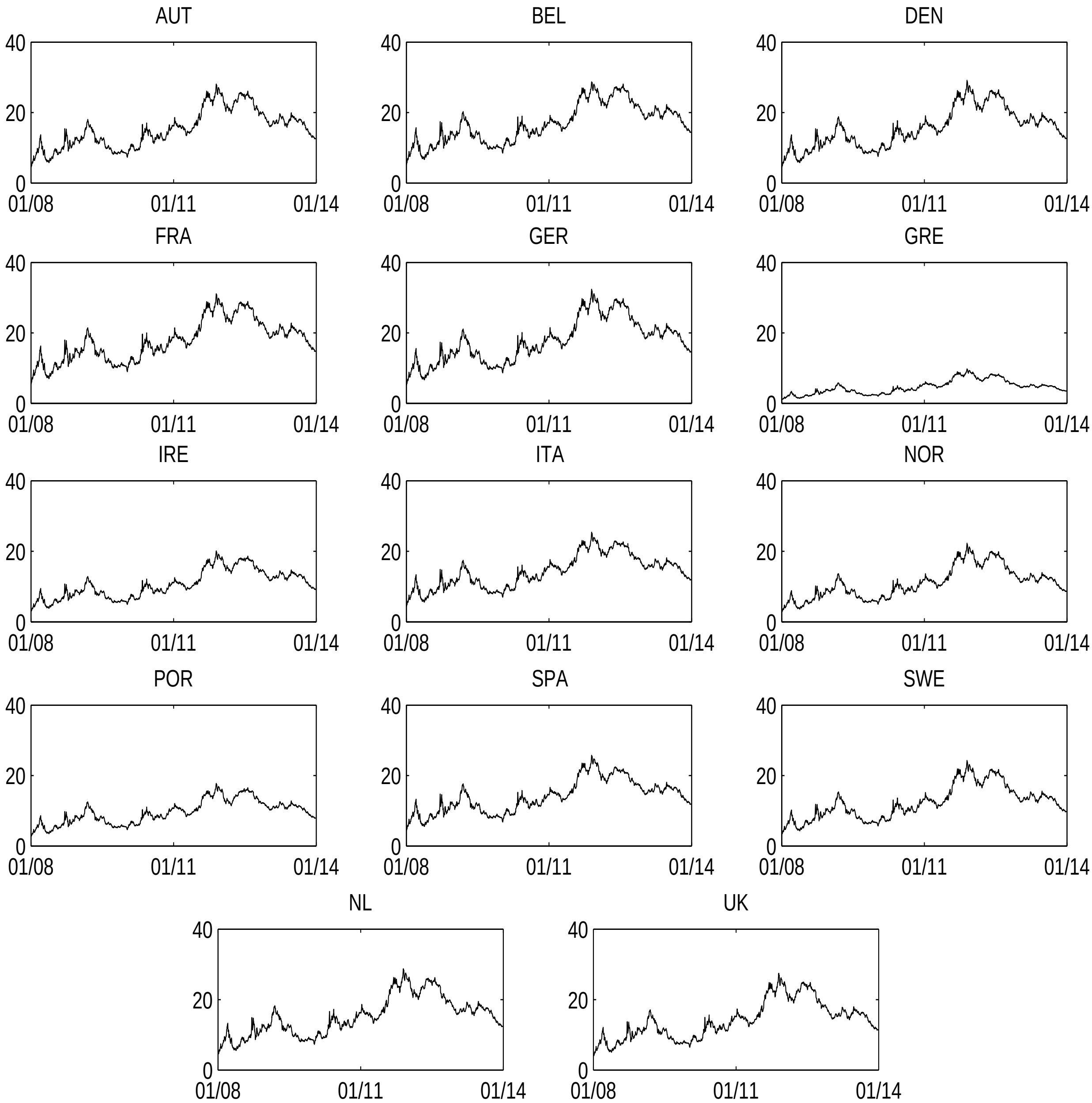
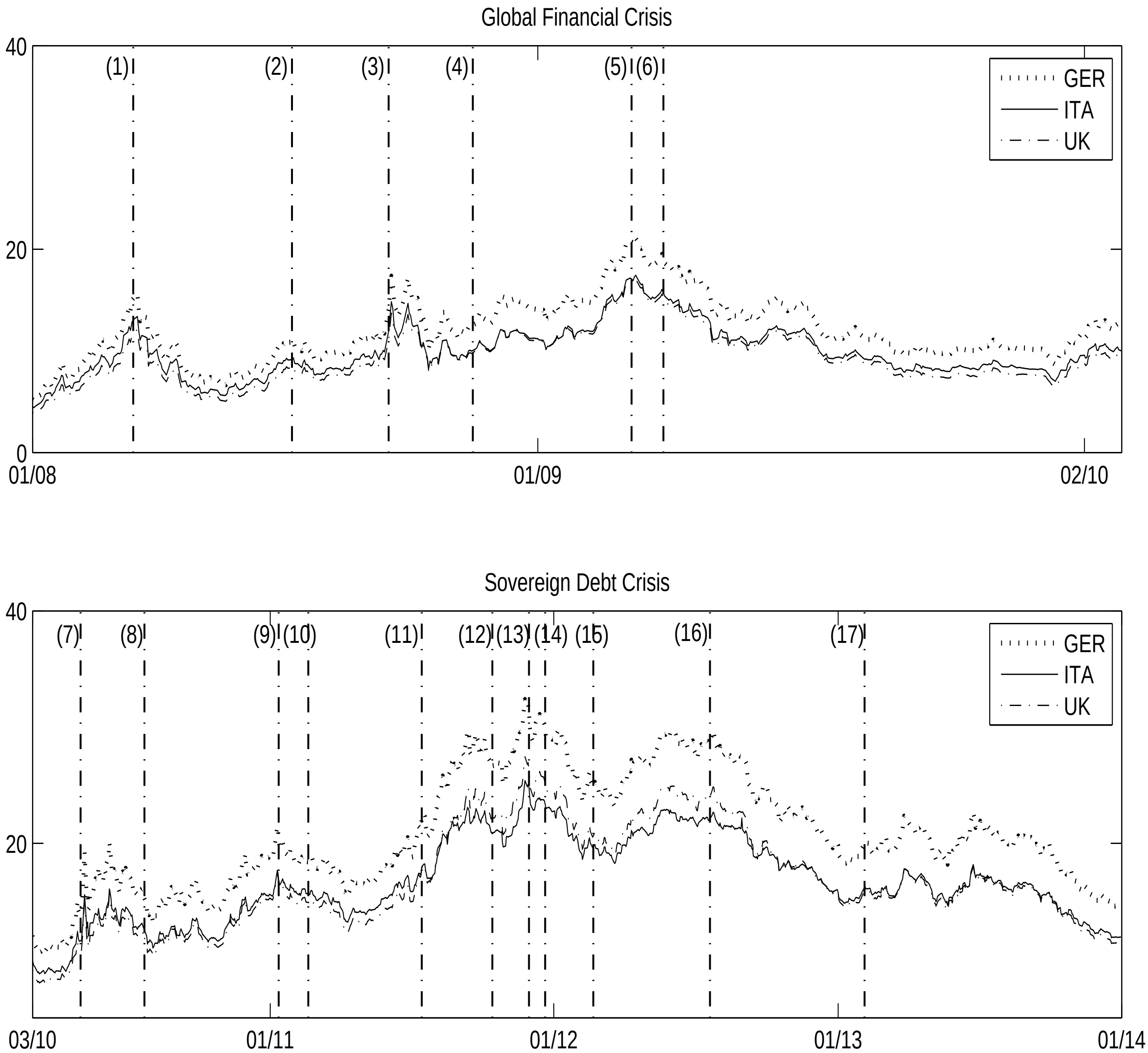


Figure 8: **Conditional joint probability of default of the banking system, given the default of a particular sovereign during the global financial crisis and the sovereign debt crisis**

The first panel presents the conditional joint probability of default of the banking system, given the default of the sovereigns listed in the legend during the global financial crisis. The second panel presents the conditional joint probability of default of the banking system, given the default of the sovereigns listed in the legend during the sovereign debt crisis. The sample period for the first panel is from 1 January 2008 to 28 February 2010. The sample period for the second panel is from 1 March 2010 to 31 December 2013. The unit of measurement for the vertical axis is %. Major events are denoted by dashed vertical lines and a brief description is provided.



(1) 14 March 2008: JP Morgan and the Federal Reserve bail out Bear Stearns.

(2) 7 July 2008: Freddie Mac, Fannie Mae plunge on capital concerns.

(3) 15 September 2008: Lehman Brothers file biggest bankruptcy after suitors balk.

(4) 15 November 2008: G20 Summit seeks to boost growth and prevent crises.

(5) 10 March 2009: US stock market hits bottom as measured by the Dow Jones Industrial Average.

(6) 2 April 2009: G20 to set up Financial Stability Board.

(7) 2 May 2010: The EA countries and the IMF agree on a €110 billion loan package to Greece.

(8) 23 July 2010: The Committee of European Banking Supervisors publishes the results of the banking stress tests.

(9) 12 January 2011: News regarding the expansion of the European Financial Stability Facility dissipated into the financial markets.

(10) 19 February 2011: G20 to focus on imbalances.

(11) 15 July 2011: The European Banking Authority publishes the results of the 2011 round of banking stress tests.

(12) 14 October 2011: G20 pledges to preserve financial stability.

(13) 30 November 2011: The Federal Reserve coordinates global effort with other central banks to lower prices on dollar liquidity swaps.

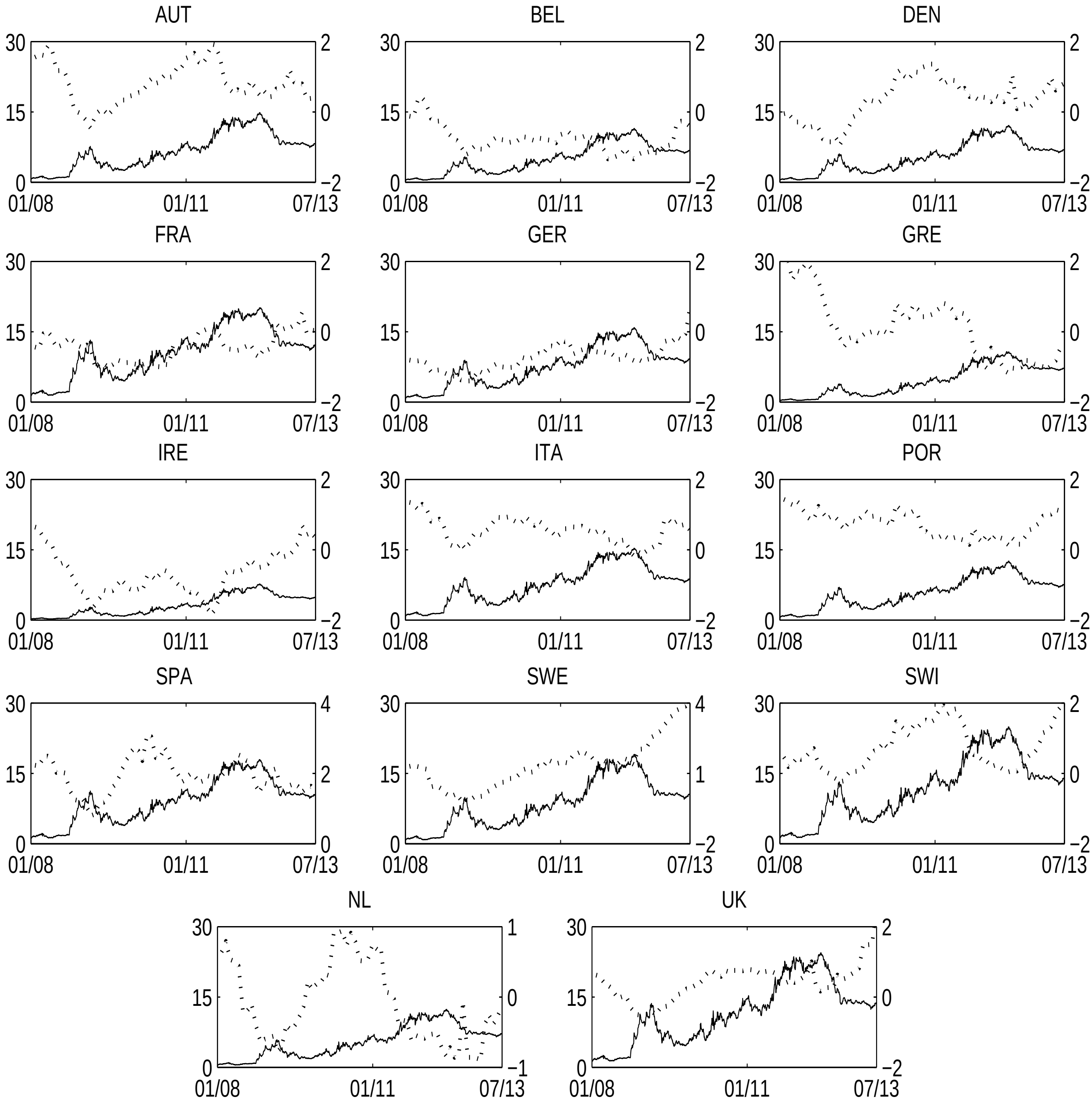
(14) 21 December 2011: The ECB implemented the first 3-year long-term refinancing operation, offering loans at low interest rates.

(15) 21 February 2012: Eurogroup agrees on second financial aid package for Greece.

(16) 20 July 2012: Eurogroup grants financial assistance to Spain's banking sector.

(17) 4 February 2013: Statement by European Commission and ECB on second review of financial assistance programme for Spain.

Figure 9: **Conditional joint probability of default of the sovereign system, given the joint default of all banks in a particular sovereign and the average DTD**
The solid line of each panel is the conditional joint probability of default of the sovereign system, given the joint default of all banks in the sovereign listed in the title of the panel. The values of the conditional joint probability of default are given on the left vertical axis in %. The dotted line of each panel is the average DTD of all banks in the sovereign listed in the title of the panel. The values of the DTD are given on the right vertical axis. The sample period is from 1 January 2008 to 1 July 2013.



C. Tables

Table 1: **List of sovereigns and banks**
This table presents the 14 sovereigns and 40 banks used in our analyses. Next to each sovereign is its abbreviated name in parentheses. The home country for each bank is also reported. We do not include Switzerland as a sovereign because its sovereign CDS contract is not informative enough for the majority of our sample period. For the same reason, we do not include any banks from Norway.

Sovereigns	Banks			
	Bank	Country	Bank	Country
Austria (AUT)	Erste Group Bank AG	Austria	Intesa Sanpaolo SpA	Italy
Belgium (BEL)	Raiffeisen Bank	Austria	Mediobanca SpA	Italy
Denmark (DEN)	Dexia SA	Belgium	UniCredit SpA	Italy
France (FRA)	KBC Groep NV	Belgium	Banco Comercial Portugues SA	Portugal
Germany (GER)	Danske Bank A/S	Denmark	Espirito Santo Financial Group	Portugal
Greece (GRE)	BNP Paribas	France	Banco Bilbao Vizcaya	Spain
Ireland (IRE)	Credit Agricole SA	France	Banco de Sabadell SA	Spain
Italy (ITA)	Natixis	France	Banco Santander SA	Spain
Norway (NOR)	Société Générale	France	Nordea Bank	Sweden
Portugal (POR)	Commerzbank AG	Germany	Skandinaviska Enskilda Banken	Sweden
Spain (SPA)	Deutsche Bank AG	Germany	Svenska Handelsbanken AB	Sweden
Sweden (SWE)	IKB Bank	Germany	Swedbank AB	Sweden
Netherlands (NL)	Alpha Bank	Greece	Credit Suisse Group	Switzerland
United Kingdom (UK)	Allied Irish Banks PLC	Ireland	UBS SG	Switzerland
	Irish Life and Permanent	Ireland	ING Groep NV	Netherlands
	Bank of Ireland	Ireland	SNS Bank Netherlands	Netherlands
	Banca Italease	Italy	Barclays PLC	United Kingdom
	Banca Monte dei Paschi di Siena	Italy	HBOS PLC	United Kingdom
	Banca Popolare di Milano	Italy	Lloyds Banking Group	United Kingdom
	Banco Popolare SC	Italy	Standard Chartered	United Kingdom

Table 2: **Sovereign correlation matrix**

This table presents the correlation matrix between the 14 sovereigns. The correlation coefficients between any two sovereigns are based on daily changes in the five-year CDS spreads of the respective sovereigns. The abbreviations of the sovereigns are listed in Table 1. All CDS contracts are denominated in US dollars and the sample period is from 1 January 2008 to 31 December 2013.

	AUT	BEL	DEN	FRA	GER	GRE	IRE	ITA	NOR	POR	SPA	SWE	NL	UK
AUT	1.00	0.68	0.68	0.68	0.66	0.09	0.48	0.56	0.46	0.38	0.55	0.64	0.72	0.65
BEL		1.00	0.60	0.78	0.67	0.16	0.58	0.72	0.39	0.53	0.73	0.45	0.66	0.56
DEN			1.00	0.61	0.62	0.12	0.45	0.54	0.46	0.37	0.51	0.66	0.66	0.58
FRA				1.00	0.72	0.16	0.51	0.70	0.42	0.48	0.69	0.46	0.65	0.53
GER					1.00	0.11	0.47	0.58	0.45	0.44	0.59	0.54	0.67	0.59
GRE						1.00	0.12	0.13	0.08	0.12	0.16	0.07	0.11	0.06
IRE							1.00	0.56	0.33	0.65	0.61	0.37	0.46	0.46
ITA								1.00	0.35	0.57	0.85	0.38	0.56	0.48
NOR									1.00	0.25	0.35	0.47	0.47	0.42
POR										1.00	0.61	0.25	0.35	0.36
SPA											1.00	0.38	0.55	0.49
SWE												1.00	0.62	0.57
NL													1.00	0.65
UK														1.00

Table 3: **Conditional joint probability of default of the banking system given the default of individual banks on specific dates**

This table presents the conditional joint probability of default of the banking system given the default of each bank in the first column. We also report the home country of each bank in the second column. The third to seventh columns give the values of the conditional joint probability of default on five specific dates. The eighth and ninth columns give the total assets and total liabilities, respectively, of each bank in 2011, in billions of euros.

Bank	Country	Conditional joint probability of default					Total assets	Total liabilities
		15 Sept 2008	10 Mar 2009	2 May 2010	25 Nov 2011	19 Dec 2013		
Erste Group Bank AG	AUT	0.084	0.133	0.094	0.201	0.091	209.30	194.12
Raiffeisen Bank	AUT	0.094	0.121	0.080	0.256	0.097	146.63	135.69
Dexia SA	BEL	0.052	0.111	0.059	0.154	0.060	412.05	412.37
KBC Groep NV	BEL	0.145	0.140	0.123	0.256	0.134	282.94	266.17
Danske Bank A/S	DEN	0.071	0.118	0.071	0.191	0.075	342.26	329.68
BNP Paribas	FRA	0.230	0.293	0.209	0.333	0.208	1955.94	1870.31
Credit Agricole SA	FRA	0.156	0.286	0.151	0.330	0.162	1718.51	1669.22
Natixis	FRA	0.108	0.119	0.146	0.404	0.164	504.50	487.11
Société Générale	FRA	0.168	0.285	0.167	0.278	0.166	1176.79	1125.68
Commerzbank AG	GER	0.182	0.335	0.180	0.277	0.153	657.61	630.23
Deutsche Bank AG	GER	0.182	0.262	0.146	0.322	0.204	2155.37	2100.71
IKB Bank	GER	0.038	0.052	0.055	0.202	0.051	31.25	30.27
Alpha Bank	GRE	0.034	0.060	0.031	0.096	0.035	57.68	56.25
Allied Irish Banks PLC	IRE	0.040	0.062	0.037	0.124	0.019	132.96	118.50
Irish Life and Permanent	IRE	0.038	0.071	0.039	0.097	0.090	71.85	68.34
Bank of Ireland	IRE	0.035	0.061	0.040	0.109	0.092	153.50	143.25
Banca Italease	ITA	0.030	0.043	0.081	0.336	0.105	10.53	8.89
Banca Monte dei Paschi di Siena	ITA	0.117	0.261	0.115	0.205	0.068	234.03	223.05
Banca Popolare di Milano	ITA	0.166	0.232	0.132	0.224	0.079	51.22	47.16
Banco Popolare SC	ITA	0.110	0.119	0.090	0.157	0.084	130.86	121.44
Intesa Sanpaolo SpA	ITA	0.158	0.242	0.131	0.230	0.162	626.90	579.14
Mediobanca SpA	ITA	0.152	0.242	0.129	0.259	0.152	74.80	67.77
UniCredit SpA	ITA	0.133	0.162	0.116	0.336	0.164	914.11	859.31
Banco Comercial Portugues SA	POR	0.097	0.147	0.078	0.148	0.075	91.92	87.54
Espirito Santo Financial Group	POR	0.076	0.126	0.075	0.198	0.092	79.53	73.54
Banco Bilbao Vizcaya	SPA	0.185	0.251	0.154	0.321	0.164	597.69	552.44
Banco de Sabadell SA	SPA	0.067	0.120	0.085	0.195	0.103	100.44	93.60
Banco Santander SA	SPA	0.178	0.249	0.169	0.325	0.163	1251.53	1162.77
Nordea Bank	SWE	0.108	0.193	0.097	0.243	0.110	716.20	688.06
Skandinaviska Enskilda Banken	SWE	0.077	0.112	0.073	0.192	0.078	264.76	252.09
Svenska Handelsbanken AB	SWE	0.118	0.196	0.112	0.285	0.112	275.42	263.22
Swedbank AB	SWE	0.058	0.090	0.070	0.195	0.071	208.39	196.62
Credit Suisse Group	SWI	0.210	0.265	0.209	0.405	0.186	861.83	819.14
UBS SG	SWI	0.151	0.194	0.159	0.351	0.196	1163.96	1120.48
ING Groep NV	NL	0.083	0.199	0.114	0.259	0.174	1270.56	1223.33
SNS Bank Netherlands	NL	0.128	0.072	0.056	0.165	0.039	128.21	123.64
Barclays PLC	UK	0.119	0.185	0.167	0.317	0.142	1560.52	1495.32
HBOS PLC	UK	0.065	0.209	0.115	0.317	0.217	568.00	540.36
Lloyds Banking Group	UK	0.166	0.207	0.117	0.228	0.156	966.05	919.46
Standard Chartered	UK	0.201	0.126	0.219	0.417	0.116	385.26	358.62

Table 4: **Decomposition of systemic risk**

This table presents the decomposition of systemic risk according to the panel regression specification in Eq. (5). The dependent variable for all seven columns is the conditional joint probability of default of the sovereign system given the joint default of all banks in a particular sovereign. The variable *LRP* is the liquidity risk premium calculated by using the daily three-month euro LIBOR/OIS (or EURIBOR/EONIA) spread; *DRP* is the default risk premium calculated by using the daily difference between the yields of 10-year euro zone industrials rated BBB and those rated AA+/AA; *SRP* is the sovereign risk premium calculated by using the daily difference between Germany's 10-year generic yield with the average of the Spanish and Italian 10-year generic yields weighted by their quarterly real GDPs; *DTD* is the average DTD of all banks within a particular sovereign; *Itraxx* is the European iTraxx index; *Market* is the EU stock market index; and *Vstoxx* is the Vstoxx volatility index. Columns (1) to (5) use the full sample of 40 banks from 14 sovereigns. Columns (6) and (7) use banks from peripheral and non-peripheral sovereigns, respectively. The sample period consists of monthly observations from 1 January 2008 to 28 June 2013. All columns use sovereign fixed effects; *t*-statistics are shown in parentheses; and the superscripts *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
						Sovereign subsample	
						Peripheral	Non-peripheral
Constant	0.043^{**}	0.042^{**}	0.040^{**}	0.043^{**}	0.038^{**}	0.033^{*}	0.036^{*}
	(2.31)	(2.30)	(2.15)	(2.30)	(2.14)	(1.86)	(1.96)
LRP	-0.016^{*}				-0.031^{***}	-0.036^{**}	-0.028^{**}
	(−1.67)				(−3.17)	(−2.25)	(−2.28)
DRP		0.220^{***}			0.274^{***}	0.226^{***}	0.298^{***}
		(6.15)			(7.42)	(3.76)	(6.36)
SRP			0.085^{**}		0.195^{***}	0.141^{**}	0.220^{***}
			(2.15)		(4.75)	(2.10)	(4.21)
DTD				-0.002^{*}	-0.003^{*}	-0.004^{**}	0.002
				(−1.68)	(−1.77)	(−2.50)	(0.63)
Itraxx	0.211^{***}	0.157^{***}	0.214^{***}	0.219^{***}	0.113^{***}	0.140^{**}	0.099^{*}
	(5.08)	(3.77)	(5.19)	(5.32)	(2.70)	(2.05)	(1.87)
Market	-1.362^{***}	-1.107^{***}	-1.268^{***}	-1.338^{***}	-0.938^{***}	-0.962^{***}	-0.934^{***}
	(−12.90)	(−10.12)	(−11.60)	(−12.8)	(−8.09)	(−5.09)	(−6.36)
Vstoxx	0.191^{***}	0.173^{***}	0.161^{***}	0.179^{***}	0.156^{***}	0.185^{***}	0.144^{***}
	(5.51)	(5.21)	(4.64)	(5.28)	(4.57)	(3.32)	(3.31)
Sovereign fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	924	924	924	924	924	330	594
Adjusted R^2	0.531	0.549	0.532	0.531	0.562	0.567	0.559
Number of banks	40	40	40	40	40	16	24
Number of sovereigns	14	14	14	14	14	5	9

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