European Banks and Sovereigns

Wedding or Divorce?

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Abstract

This paper uses a conditional measure of systemic risk, the conditional joint probability of default, to quantify the effects of a sovereign default on the European sovereign and banking system. Our systemic risk indicator not only reflects individual default risk characteristics but also captures the underlying interdependent relationships between sovereigns and banks in a multivariate setting. Based on our measure, we document a substantial grouping effect whereby core European sovereigns maintain the highest marginal contribution to systemic default risk, while peripheral sovereigns maintain the lowest. We show that the conditional joint default risk of the European banking system reached historical highs of 29% during the midst of the sovereign debt crisis in late 2011. We attribute this heightened risk to rapid increases in the sovereign risk premium coupled with a steady rise in objective default rates. When investigating the determinants of conditional joint default risk, we document a significant ‘too-many-to-fail’ effect for both the sovereign and banking system. In addition, we show that sovereign size has substantial explanatory power in predicting the one-year-ahead conditional joint probability of default, thereby indicating the existence of the ‘too-big-to-fail’ phenomenon.

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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 the current economic situations of Greece, Ireland, Italy, Portugal, and Spain could potentially destroy the stability of the European financial system. As the threat of financial contagion spreads throughout Europe, 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 a sovereign default on the European sovereign and banking system.

Systemic risk is associated with the risk that arises due to the interactions and interconnections between financial entities. Although there is currently no widely accepted definition of systemic risk, a recurring theme throughout the systemic risk literature is that true systemic events impact the entire financial system (Billio et al., 2012). In this paper, we specifically focus on the systemic risk of the European sovereign and banking system. We are motivated by the fact that Europe has been inundated by the global financial crisis and the sovereign debt crisis, and that a collapse of the EA may well lead to another global recession. Although sovereign defaults are rare events, they have serious repercussions for the involved entities and third parties if the impending defaults are not avoided (Arteta & Hale, 2008; Panizza & Zettelmeyer, 2009). However, if a systemic crisis were to materialize in the EA, sovereign defaults would only be one of many contributing factors; the European banking system would also be severely impacted. Indeed, banks that engage in credit risk activities are perceived by the market to be substantially riskier during systemic crises (Nijskens & Wagner, 2011). Despite the overwhelming consequences, a unified measure of systemic risk that quantifies the feedback effects in a multivariate context is lacking. Thus, there are three main research objectives of this paper: First, we construct a conditional measure of systemic risk that attempts to capture the many facets of an adequate systemic risk indicator: consistency, flexibility, forward-looking focus, correspondence with empirical data, and financial regulatory suitability (Gramlich & Oet, 2011). Second, we ensure that our systemic risk measure is applicable in a true multivariate setting consisting of both sovereigns and banks. Third, we empirically implement our systemic risk measure by
using a sample of 10 EA sovereigns and 26 EA banks, over the sample period of 2008 to 2013. Our measure of systemic risk can be intuitively interpreted as the conditional joint probability of default of an entity, given the default of other entities within the system.\(^1\) As such, our measure 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. We construct our systemic risk indicator in three steps. First, we recover the marginal probabilities of default \((PoD)\) from credit default swap (CDS) spreads by bootstrapping a standard cumulative survival probability model (Hull & White, 2000). We derive our systemic risk measure based on CDS spreads because they are forward-looking and they readily incorporate investors’ perceptions of default risk. This is an important characteristic to have in an ideal systemic risk indicator, since systemic shocks often have dire consequences for investors. For example, Kole et al. (2006) show that systemic crises significantly alter an investor’s asset allocation decisions and ignoring systemic risks impose substantial costs on an investor’s portfolio. Furthermore, systemic risk indicators, based on CDS spreads, are generally superior to those derived from interbank rates or equity prices (Rodríguez-Moreno & Peña, 2013). Second, we use the newly developed consistent information multivariate density optimization (CIMDO) methodology introduced by Segoviano (2006) to implement a time-varying dependence structure in the form of a multivariate probability distribution from which we estimate the joint probability of default \((JPoD)\). This approach makes it possible to study the full extent systemic default risk, since it grants us immense flexibility in the choice of conditioning. Finally, we combine individual default risk characteristics with joint default risk dynamics to construct the conditional joint probability of default \((CoJPoD)\).

Following the global financial crisis, theoretical developments of systemic risk indicators have undergone rapid growth. Four categories of papers can be identified based on the procedures that they use to derive their systemic risk indicator. The structural approach directly examines the balance sheet items of an institution to determine its contribution to systemic risk. This approach is based on the assumptions of the Merton (1974) model and typically asserts strong

\(^1\)Similar to Adrian & Brunnermeier (2011) and Radev (2012), we define entities as either a sovereign or a bank. The system is defined to be a portfolio of its constituent entities. For example, the European sovereign system is a portfolio of EA sovereigns; likewise, the European banking system is a portfolio of EA banks.
assumptions on the capital structure of financial institutions in the form of static dependence structures. Papers that employ this technique (or more generalized versions of it) include Lehár (2005), Bartram et al. (2007), and Gray et al. (2007). The reduced-form approach diverts attention away from firm-specific information and focuses on the actual default process. Adrian & Brunnermeier (2011) use quantile regression to construct ΔCoVaR, which represents an institution’s marginal contribution to the overall systemic risk of the financial system. Computationally, ΔCoVaR is defined as the difference between the VaR of the financial system conditional on the distress of a particular financial institution and the VaR of the financial system conditional on the institution being in its median state. López-Espinosa et al. (2012) modify the basic CoVaR methodology to incorporate asymmetric and recapitalization effects, as well as structural changes due to the global financial crisis. Girardi & Ergün (2013) generalize the definition of CoVaR by allowing the returns of an institution to exceed its VaR, as opposed to being exactly equal to its VaR. Acharya et al. (2010) utilize the equity returns of financial institutions and aggregate returns of the entire financial market to construct the marginal expected shortfall (MES). MES can be interpreted as the average losses of a particular institution when the returns on the entire market fall below a certain threshold. As an extension to the MES, Brownlees & Engle (2012) construct a systemic risk index, termed SRISK, that captures an institution’s size, leverage, as well as its MES. The SRISK index represents the capital shortage of an institution conditional on the entire financial market suffering large losses. Puzanova & Düllmann (2013) model the banking system as a credit portfolio consisting of systemically intertwined banks and measure systemic risk as the expected shortfall of this portfolio. Their measure can be interpreted as the expected losses to investors, given the occurrence of a systemic event. Huang et al. (2009) propose a measure of systemic risk, the so-called distress insurance premium (DIP), based on the CDS spreads and equity prices of individual banks. The DIP can be interpreted as a hypothetical insurance premium to cover distressed losses in the banking system. Black et al. (2013) empirically implement the DIP methodology to measure the level of systemic risk in the European banking system.

While the reduced-form approach attempts to quantify systemic risk by examining the historical distribution of returns, the copula-based approach directly measures an institution’s probability
of tail risk by using derivative securities (e.g., CDS contracts) that are extremely sensitive to this risk. The characterizing feature of this approach lies in extracting individual probabilities of default from CDS spreads, which are then transformed into joint probabilities of default by specifying an underlying dependence structure (otherwise known as a copula). Avesani et al. (2006) use a multivariate Gaussian copula to determine the default probabilities of an nth-to-default CDS basket of large complex financial institutions. Goodhart & Segoviano (2009) utilize the CIMDO copula to create a set of banking stability measures that encapsulates a series of indicators ranging from the joint default risk of the banking system to the default risk associated with individual banks. Radev (2012) generalizes the CIMDO copula to a multivariate setting and utilizes the change in the conditional joint probability of default to examine cascade effects from small to large EA sovereigns by following the propagation of default risk throughout the European sovereign system. Zhang et al. (2012) use a multivariate framework based on a dynamic generalized hyperbolic skewed-$t$ copula to capture the skewed and fat-tailed nature of systemic default risk. Finally, in contrast to the aforementioned approaches, several recent papers derive systemic risk measures through the use of empirical and econometric techniques. Billio et al. (2012) use principal components analysis and pairwise Granger-causality tests to measure the interconnections between entities of the financial system. Duca & Peltonen (2013) employ a composite mix of five financial variables in developing a financial stress index to identify and predict the occurrence of a systemic financial crisis. Using a lag-linear regression model, Oet et al. (2013) construct the systemic assessment of financial environment early warning system to help forecast and prevent systemic crises. Gravelle & Li (2013) utilize multivariate extreme value theory to estimate an institution’s contribution to systemic risk, defined as the simultaneous crash of several institutions’ stock prices.

Our paper effectively falls under the copula-based approach and can be most closely identified with the works of Radev (2012) and Black et al. (2013), since these papers also examine systemic risk in an European context. However, there are three inherent differences between our study and these two papers. First, Radev (2012) primarily examines the level of systemic risk in the European sovereign system, while Black et al. (2013) focus solely on the systemic default risk of the European banking system. In contrast, we use the conditional joint probability of
default to quantify the level of systemic risk in both the European sovereign and banking system. Second, Radev (2012) attempts to measure systemic risk by conditioning on the default of peripheral European sovereigns, while Black et al. (2013) measure systemic risk by conditioning on the entire European banking system suffering large losses.\footnote{The authors define financial distress as the situation when at least 10\% of total liabilities in the banking system defaults.} Contrarily, we fully exploit the conditional flexibility of our systemic risk indicator by conditioning on a multitude of events that are economically meaningful. Third, Black et al.’s (2013) empirical methodology consists of examining the determinants and decomposition of the DIP, and assessing the predictive ability of a range of accounting and market based bank-specific financial variables. We extend their empirical analyses by generalizing from a bank-specific context to a sovereign and bank setting.

Our main contribution is that we use a conditional measure of systemic risk to quantify the default risk contributions of EA sovereigns on the European sovereign and banking system. In a multivariate setting, our systemic risk indicator has several advantages over reduced-form measures such as MES and CoVaR. Specifically, both MES and CoVaR lack a forward-looking focus, since they predominantly rely on historical stock market returns and firm specific data. As noted by Idier et al. (2011), MES conditions upon infrequent but not extremely rare events in the market. Similarly, CoVaR requires an estimation of the return distribution from limited historical time series returns. This approach relies on very strong assumptions regarding the behaviour of the tail region in the return distribution (Giglio, 2012). Therefore, for both measures, 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 the credit-worthiness of an institution (Predescu et al., 2004). 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 indicator. MES and CoVaR also condition on 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 only provides one perspective out of many other possible choices. Contrarily, one of the most important features of our conditional measure of
systemic risk is its flexibility in conditioning. Our procedure enables us to empirically investigate many aspects of systemic risk including individual and aggregate systemic default risk, intra-system systemic risk, and inter-system systemic risk.

We also make contributions at the methodological level by utilizing the newly developed CIMDO methodology (Segoviano, 2006) to examine the spillover effects of systemic default risk between sovereigns and banks in a true multivariate setting. As mentioned earlier, the structural approach (Merton, 1974) requires specification of an institution’s capital structure; hence, this particular procedure becomes overwhelmingly tedious in a multivariate context, since there are numerous ways to categorize sovereign capital structure. Similarly, CoVaR, MES and the DIP require estimation of an institution’s asset return distribution. Thus, these measures are not suitable for measuring systemic risk in a sovereign context because explicit definition of sovereign assets and liabilities are needed. By applying the CIMDO methodology, we shift the focus away from capital structure and directly view the EA as a joint distribution of its constituent entities. To account for tail risk, the CIMDO methodology adjusts the tail region of the underlying joint distribution so that it is always consistent with empirical data. Consequently, we are able to derive our measure of systemic risk in a multivariate setting because we circumvent the issue of having to define sovereign capital structure. Another drawback of MES and CoVaR is that they are restricted to two types of static interdependent relationships: the default risk between two individual entities or the distress dependencies between an entity and the financial system. In contrast, 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, by specifically deriving a dynamic joint probability distribution, we are able to capture all interactions and co-movements between every entity within the system at each point in time.

Our empirical implementation contributes to the financial stability literature by examining the explanatory power and predictive abilities of a range of credit risk variables and macroeconomic fundamentals on the conditional joint probability of default of the European sovereign and banking system. We find that marginal default risk characteristics, bank interdependencies, and uncertainty in the degree of interdependence all play an important role in determining the
conditional joint default risk for the European banking system. In particular, individual probability of default appears to be the dominant factor, since it alone explains almost 98% (85%) of the variation in the conditional joint probability of default for the banking (sovereign) system. At the same time, we find evidence for the existence of the ‘too-many-to-fail’ phenomenon for both the sovereign and banking system, suggesting that the severity of a financial crisis depends not only on the size of defaulting entities but also on the number of entities defaulting. With respect to predictive power, we find that a sovereign’s economic performance, uncertainty in economic prospects, size, debt obligations, and liquidity buffers all have significant explanatory power in predicting the one-year-ahead conditional joint default risk of the sovereign and banking system. Most notably, we find strong evidence for the presence of the ‘too-big-to-fail’ effect; large sovereigns are less likely to default during a systemic crisis and if they do default, then catastrophic ripple effects are felt throughout the sovereign and banking system.

Finally, we contribute to the emerging strand of literature that examines the decomposition of systemic risk by decomposing our systemic risk measure into physical probabilities of default and risk premium components. Recent papers have focused on the decomposition of the DIP. For example, Huang et al. (2010) find that the systemic risk of Asia-Pacific banks were significantly driven by both the default risk premium and the liquidity risk premium. Similarly, Huang et al. (2011) show that these two risk premiums were also major drivers of systemic risk for large US banks throughout the global financial crisis. Most recently, Black et al. (2013) document a decrease in significance of the default risk premium and the liquidity risk premium, but a dramatic increase in the sovereign risk premium. The authors show that the sovereign risk premium was the most influential risk factor in determining the systemic risk of European banks during the sovereign debt crisis. In contrast to these papers, our source of decomposition is the conditional joint probability of default. Furthermore, we decompose our systemic risk measure in the European sovereign and banking system. Hence, in both settings, we are able to investigate how much of our measure is driven by the pure credit qualities of European banks and how much is steered by changes in market risk perceptions. Consistent with Black et al. (2013), we find that the sovereign risk premium appears to be the dominant factor in driving the conditional joint default risk of the European sovereign and banking system, implying that
there are large differences in creditworthiness between peripheral and core sovereigns. We also document a steady increase in physical probabilities of default for both the sovereign and banking system. This finding is consistent with the idea that the physical stress placed on Europe’s banking system combined with the deterioration in the macroeconomic performance of the European sovereign system has led to substantial downward revisions in Europe’s economic fundamentals.

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 and provides some descriptive analyses. 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 (Schwarcz, 2008). We follow the view that systemic risk can be quantified through probabilistic measures in both the sovereign and banking system (Radev, 2012). We begin by constructing the marginal probability of default \( \text{PoD} \) of the system. Assume there are \( n \) entities (or institutions) in the system and let \( X_1, X_2, \ldots, X_n \) denote the random variables corresponding to the natural logarithm of assets of institution \( I_1, I_2, \ldots, I_n \), respectively. Following the structural approach (Merton, 1974), we define an institution to be in default if its logarithm of assets exceeds a certain threshold, which we denote as \( X_{id}^i \). The marginal probability of default is given by:

\[
\text{PoD}_i = P(X_i \geq X_{id}^i) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} p(x_1, x_2, \ldots, x_n) dx_1 dx_2 \cdots dx_i \cdots dx_n
\]

(1)

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

\(^3\)For convenience, the default region is defined to be in the right tail of the density function.
The above definition gives the theoretical probability of default of institution $I_i$. However, since the underlying asset structure of an institution is constantly changing due to the general volatility of the business cycle, the default threshold will also change throughout time. Following Segoviano (2006), we define the fixed time average default threshold of institution $I_i$ as:

$$X_{i_d}^i = \Phi^{-1}(1 - \overline{PoD}_i)$$

(2)

where $\Phi^{-1}(\cdot)$ denotes the standard inverse normal cumulative function and $\overline{PoD}_i$ is the time average empirical probability of default of institution $I_i$ estimated from bootstrapping CDS spreads.

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

$$JPoD\{I_1, I_2, \ldots, I_n\} = P( X_1 \geq X_{I_1}^{I_1}, X_2 \geq X_{I_2}^{I_2}, \ldots, X_n \geq X_{I_n}^{I_n})$$

$$= \int_{X_{I_1}^{I_1}}^{\infty} \cdots \int_{X_{I_n}^{I_n}}^{\infty} \int_{X_{d}^{I_1}}^{\infty} \cdots \int_{X_{d}^{I_n}}^{\infty} p(x_1, x_2, \ldots, x_n) dx_1 dx_2 \cdots dx_n$$

(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. An important feature of the $JPoD$ is that it captures the underlying dependence structure between every entity. Hence, in times of financial distress, the $JPoD$ of the system could be much larger than the average $PoD$ of the individual entities due to the $JPoD$ capturing the distress dependencies between the entities. From a computational perspective, the $JPoD$ is calculated by integrating over all regions of default, whereas the $PoD$ is determined by integrating over one particular region of default.

We now combine the marginal probability of default and joint probability of default through Bayes’ theorem to produce the conditional joint probability of default ($CoJPoD$) of the system,

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4We use the notation $\{I_1, I_2, \ldots, I_n\} = system$, so $JPoD_{\{I_1, I_2, \ldots, I_n\}} = JPoD_{system}$.  

given the default of institution $I_k$: $^5$

$$\text{CoJPoD}_{\{I_1, \ldots, I_{k-1}, I_{k+1}, \ldots, I_n\}|I_k}$$

$$= \text{CoJPoD}_{\text{system}|I_k}$$

$$= P \left( X_1 \geq X_{d}^{I_1}, \ldots, X_{k-1} \geq X_{d}^{I_{k-1}}, X_{k+1} \geq X_{d}^{I_{k+1}}, \ldots, X_n \geq X_{d}^{I_n} | X_k \geq X_{d}^{I_k} \right)$$

$$= \frac{P \left( X_k \geq X_{d}^{I_k} \right)}{P \left( X_k \geq X_{d}^{I_k} \right)}$$

$$= \frac{\text{JPoD}_{\{I_1, I_2, \ldots, I_n\}}}{\text{PoDi}_k}$$

$$= \frac{\text{JPoD}_{\text{system}}}{\text{PoDi}_k} \quad (4)$$

This expression shows that the conditional joint probability of default is simply the ratio of the joint probability of default of the system and the marginal probability of default of a particular institution. Thus, we can interpret $\text{CoJPoD}_{\text{system}|I_k}$ as the default likelihood of the remaining institutions within the system, given the default of a particular institution.

The marginal contribution of institution $I_k$’s default on the overall systemic risk of the system can be derived by comparing the system’s conditional joint probability of default with its unconditional joint probability of default. We define the change in the conditional joint probability of default as:

$$\Delta \text{CoJPoD}_{\text{system}|I_k} = \text{CoJPoD}_{\text{system}|I_k} - \text{JPoD}_{\text{system}} \quad (5)$$

The rationale behind the above formulation is that we can consider $\Delta \text{CoJPoD}$ as a relative measure of systemic risk that reflects the probabilistic difference between two extreme states of the system. Suppose institution $I_k$ is a key figure in the system such that its default incurs large financial stress on the remaining non-defaulting entities. Given the default of institution $I_k$, we can expect $\text{CoJPoD}_{\text{system}|I_k}$ to be very large. However, we need a benchmark to gauge just exactly how ‘bad’ things can get; an obvious choice for comparison is the joint probability of

$^5\{\text{system}\setminus I_k\}$ denotes the set of institutions in the system excluding institution $I_k$. 

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default of the system excluding institution $\tilde{I}_k$.\footnote{Such a comparison is equivalent to assuming independence between the system and the defaulting institution.}

2.2. **Estimating Marginal Probabilities of Default**

To estimate the marginal probabilities of default, we apply a bootstrapping procedure based on the standard survival probability model introduced by Hull & White (2000). We utilize 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. Following prior literature, we set a constant recovery rate of 40% (Sturzenegger & Zettelmeyer, 2005). 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 equate the premium leg with the payoff leg.\footnote{A CDS contract has two “legs”, a premium leg and a payoff leg. The former is the premium that the buyer pays to insure themselves against possible defaults of the reference entity. The latter represents the payoff to the buyer in the case where 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.} Hence, the no-arbitrage condition is satisfied throughout the procedure. Since we use a maximum maturity of five years for CDS spreads, our resulting PoD values are cumulative five-year probabilities of default. We annualize these PoD values so that they form a one-year perspective. Section A.1 of the Appendix provides a detailed explanation of the bootstrap algorithm.

In a sovereign and banking context, our bootstrapping procedure has several advantages over other alternatives. First, Merton’s (1974) structural approach can be used to derive probabilities of default based on the balance sheet items of an institution. Specifically, one can calculate the distance to default (DTD) of an institution based on the institution’s asset value, volatility of the asset value, and book value of liabilities. By specifying an asset distribution for the institution, one can transform the DTD into a probability of default. The disadvantage of the...
structural approach is that it is extremely difficult to specify a proper asset distribution, since asset values and volatilities are unobservable. Even if assumptions are made regarding the asset distribution, the resulting probabilities of default represent physical probabilities of default, since they are derived from the book value of balance sheet items. Since our bootstrapping process utilizes market traded CDS spreads, we are able to derive risk-neutral probabilities of default that contain not only physical probabilities of default but also any associated risk premium components.

Second, probabilities of default can be estimated from the prices of out-of-the-money call or put options using the fundamental theorem of asset pricing (Neftci, 2008). However, this approach is inapplicable in a sovereign context, since no options are traded on sovereigns. Furthermore, in a banking context, some institutions may not trade equity options or option prices may be unavailable at particular strike prices for those that do trade equity options. Since CDS contracts are traded on sovereigns and banks, we not only are able to derive probabilities of default for both the sovereign and banking system but also examine the interactions between the two systems. Third, we prefer CDS spreads over bond yields since the latter is more likely to be affected by liquidity and flight-to-safety issues. In addition, during times of distress, governments often intervene in the bond market, thereby distorting the probabilities of default.  

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.

The most standard approach to modelling default risk centres upon Merton’s (1974) structural model. Under this framework, we assume an institution’s logarithm of assets follow a normal distribution and evolve stochastically throughout time. Furthermore, the dependence structure between multiple institutions is assumed to follow a multivariate normal distribution but

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8The Securities Markets Programme initiated by the European Central Bank (ECB) on 10 May 2010 is one such example.
remains static throughout time. Subsequent empirical research has shown that normal distributions fail to adequately capture tail risk and dependence structures are inherently dynamic compositions (Goodhart & Segoviano, 2009). Other approaches to modelling joint default risk utilizes dynamic skewed-$t$ distributions (Zhang et al., 2012) and other fat tailed models (see Bams & Wielhouwer (1999), Yamai & Yoshiba (2002), Brownlees & Engle (2012), Cai et al. (2012), and Girardi & Ergün (2013) amongst many others). However, the availability of data becomes a major concern, since the calibration of these parametric distributions relies on the evolution of the institution’s capital structure. Therefore, in limited data environments, imposing parametric dependence structures becomes a challenging procedure. In a sovereign and banking context, marginal PoD values provide only partial information regarding the default risk of the system; we are still unable to observe the system’s joint default risk. In this situation, parametric models would assume more information than provided and incorrectly convert an under-identified system into a well-identified system. As a result, any subsequent inferences are inherently biased.

We utilize the CIMDO methodology (Segoviano, 2006) for recovering multivariate joint distributions when faced with incomplete information sets. The CIMDO procedure relies on the basic assumptions of the structural model but reverses the process. Instead of assuming parametric distributions to fit available information, the CIMDO approach uses all available data to calibrate a non-parametric distribution. Therefore, our procedure minimizes the possibility of misspecification and ensures that the resulting distribution is always consistent with empirical data. In contrast to the standard structural model, which assumes a fixed dependence structure with time varying default thresholds, we maintain our initial assumption of fixed default thresholds as per Eqn. 2 but allow for a time varying dependence structure. 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 as sovereign assets or liabilities when quantifying sovereign default risk. Since we effectively reverse-engineer the joint probability distribution describing the system, we can simply rely on the bootstrapped probabilities of default to proxy for the data generating process of sovereign capital structure. Section A.2 of the Appendix outlines the CIMDO procedure.

In order to solve the CIMDO procedure, 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. Following Radev (2012), we use the multivariate normal distribution as the prior and estimate the variance-covariance matrix by using the correlation coefficients between the daily changes in the five-year CDS spreads of sovereign and bank CDS contracts. The moment consistency constraints refer to restrictions of the form shown in Eqn. 1 where we replace the theoretical probabilities of default with our bootstrapped $PoD$ values. Finally, we use the Kullback-Leibler (Kullback, 1956) measure of cross-entropy to solve for the optimal posterior distribution. Section A.3 of the Appendix provides the solution to the CIMDO procedure under the GCE method.

2.4. Economic Decomposition of Systemic Risk Indicator

Using a market-based instrument such as CDS spreads to derive $CoJPoD$ directly implies that our measure is risk-neutral by construction. Hence, we can decompose our measure 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 et al. (2009) purport that during periods of high volatility, the risk premium components tend to dominate CDS spreads. Given that CDS spreads is the main ingredient for constructing $CoJPoD$, it is interesting 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 DTD metric to proxy for physical probabilities of default. In a banking context, the DTD measures how far an institution is away 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 lower physical probability of default. Estimation of DTD requires knowing the market value of the assets and the volatility of the assets, both of which are unobservable. We follow Crosbie & Bohn (1998) and use the observable value and volatility of an institution’s equity to solve for the unknown parameters in a Black-Scholes option pricing framework. The DTD measure bears 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 DTD to proxy for physical default probabilities since it is a metric based solely on the balance sheet items of an institution, therefore it represents the pure credit quality of the institution. Section A.4 of the Appendix outlines the procedure that we use to estimate the DTD.

Following Black et al. (2013), we examine three prevalent risk premiums. First, we proxy for the default risk premium by computing the daily difference between the yields of ten-year euro zone industrials rated BBB and those rated AA+/AA (Chen et al., 2009). Second, we proxy for the liquidity risk premium by using the daily three-month euro LIBOR/OIS (or EURIBOR/EONIA) spread (Brunnermeier et al., 2009). Third, we proxy for the sovereign risk premium by computing the daily difference between Germany’s ten-year generic yield with the average of the Spanish and Italian ten-year generic yields weighted by their quarterly real 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 and Descriptive Analyses**

3.1. **Data**

Our sample consists of 10 EA sovereigns and 26 EA banks, as shown in Tables 1 and 2, respectively. Our sample period spans from 1 January 2008 to 28 February 2013, allowing us to compare the level of systemic risk from the global financial crisis through to the sovereign debt crisis. We use USD-denominated (EUR-denominated) CDS contracts of maturities one to five years for sovereigns (banks). Daily CDS mid rate spreads are obtained from Datastream. We prefer USD-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 comparable measures between sovereign and bank CDS contracts, we set the euro as our base currency; thus, any CDS contracts denominated in USD will be transformed into an euro equivalent by using the historical daily EUR/USD 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 Datastream. Subsequently, we construct \( PoD, JPoD, CoJPoD, \) and \( \Delta CoJPoD \) on a daily basis. As part of the CIMDO procedure, we proxy for the sovereign correlation matrix by calculating correlation coefficients based on daily changes in the five-year CDS spreads of the sovereigns in our sample. We choose a maturity of five years since these CDS contracts are the most liquid and actively traded contracts on the market. The correlation structure between the 10 EA sovereigns is shown in Table 3. For the balance sheet data used to construct DTD, including total liabilities, total market value of equity, and the risk-free rate, we use Datastream. See Table 4 for details on all the data that we use in this paper.

3.2. **Descriptive Analyses**

Table 5 presents a summary of seven key default risk variables for the 10 EA sovereigns and 26 EA banks in our sample. Market-based variables include sovereign CDS spreads (\( Sov_{CDS} \)), bank CDS spreads (\( Bank_{CDS} \)), sovereign risk-neutral probabilities of default (\( Sov\ PoD \)),
and bank risk-neutral probabilities of default (Bank PoD). Balance sheet derived variables include bank distance to default (Bank DTD), total book value of assets (Total Assets), and total book value of liabilities (Total Liabilities). The core European sovereigns consist of Germany (GER), France (FRA), Netherlands (NL), Austria (AUT), and Belgium (BEL). The peripheral sovereigns include Spain (SPA), Ireland (IRE), Italy (ITA), and Portugal (POR).\footnote{We purposely leave out Greece (GRE) for our descriptive analyses since we do not include any Greek banks in our sample. The is because several major Greek banks are owned by French banks; thus, the systemic risk of Greek banks are absorbed into that of French banks.} We examine the evolution of these variables through two periods. Period 1, denoted (1), is the financial crisis from 1 January 2008 to 31 December 2009. Period 2, denoted (2), includes the recovery period and the sovereign debt crisis from 1 January 2010 to 28 February 2013.

As can be seen immediately from Table 5, an increase in CDS spreads from period 1 to period 2 is accompanied by an increase in the risk-neutral probabilities of default for both the sovereign and banking system. This is not surprising, since the risk-neutral PoD values are directly bootstrapped from the corresponding CDS spreads. The core sovereigns of Germany, France, and the Netherlands maintained the lowest sovereign CDS spreads and PoD values in period 1 relative to peripheral sovereigns such as Ireland, Italy, Portugal, and Spain. A rise in sovereign CDS spreads and PoD values in period 2 is seen for all sovereigns, but especially for peripheral sovereigns such as Ireland and Portugal. For example, Ireland’s sovereign CDS spreads increased from 127.65 basis points (bps) to 486.67 bps, while Portugal’s spreads increased to a staggering 659.35 bps. On a descriptive level, this observation indicates that, on average, market participants perceive peripheral sovereigns to be much riskier than core sovereigns. In addition, we notice significant differences in market sentiments regarding the default risk of the banking system. For example, German banks are perceived to be extremely safe with only 1.59% probability of default in period 1 and 2.65% in period 2. In stark contrast, Irish banks are considered excessively risky throughout both periods, peaking at 12.37% probability of default in period 2. Overall, the average CDS spreads and PoD values of the banking system are generally higher than those of the sovereign system for both periods. This observation aligns with the notion that individual banks are more prone to liquidity issues and credit events, whereas sovereigns are more likely to receive bailout packages. Interestingly, banks residing in peripheral...
eral sovereigns such as Italy and Portugal were initially perceived to be as safe as the banks in Germany and France, as reflected by similar CDS spreads and PoD values during period 1. However, consistent with the plummeting market confidence of European investors during the sovereign debt crisis, we witness a dramatic rise in the CDS spreads and PoD values of Italian and Portuguese banks in period 2.

Fig. 1 presents the time variation in average sovereign and bank PoD values (Panel A), and bank DTD (Panel B). The most immediate observation is that bank PoD values generally move in the opposite direction to bank DTD. This implies that, on average, increases in the risk-neutral probabilities of default are accompanied by increases in the physical probabilities of default. A relative comparison of sovereign and bank PoD values indicates that bank probabilities of default dominated the majority of the global financial crisis. Bank default risk continued to overshadow sovereign default risk throughout the recovery period of late 2009 to early 2010. From 2010 onwards, we see a dramatic rise in sovereign default risk that led to an overlap between sovereign and bank probabilities of default. This finding highlights the onset of both a sovereign debt crisis and a banking crisis. Towards late 2011, we notice a major decoupling between sovereign and bank probabilities of default, indicating a sizable divergence in market expectations between sovereign and bank default risk. This result may be due not only to widespread investor doubts regarding the inability of European governments to finance their sovereign debt but also to concerns about whether the EA as a whole can support its constituent members.

Fig. 2 presents the time variation in another key default risk variable: equity return correlation. Prior studies have often used stock return correlations to measure the degree of interdependence (or equivalently, interconnectedness) between financial entities (Nicolo & Kwast, 2002; Forbes & Rigobon, 2002; Chiang et al., 2007; Corsetti et al., 2010). Thus, in our subsequent empirical analyses, we use equity (stock market) return correlations to proxy for the level of interdependence between banks (sovereigns). Panel A presents the average pairwise correlation over the full sample of 26 EA banks. As can be seen, there is little dispersion in the average correlation structure over time, indicating that the level of interdependence between banks was relatively stable throughout the global financial crisis and sovereign debt crisis. In Panel B, we present the
average pairwise correlation of banks sorted by their originating sovereign. Immediately, we see that average equity correlations exhibit large cross-sectional heterogeneity at each point in time. Banks in Ireland, Portugal, and Germany tend to have fluctuating correlations over time, whereas the banks in the remaining sovereigns have similar levels of correlations. Another interesting observation is that the average correlation during the global financial crisis tended to be slightly higher than that during the sovereign debt crisis. This finding is consistent with European banks reacting in a uniformed manner to shocks from the United States during the global financial crisis but exhibiting dispersed reactions during the sovereign debt crisis due to unequal distributions in economic growth, varying liquidity conditions, and volatile levels of government debt.

4. **Empirical Results**

We apply the methodology outlined in Section 2 to examine the level of systemic default risk in the European sovereign and banking system. Furthermore, we aggregate our systemic risk indicator for the banking system and investigate its evolution throughout the global financial crisis and the sovereign debt crisis. We also explore the determinants of our systemic measure through the use of fundamental credit risk variables. Following on, we examine the decomposition of our CoJPoD measure into physical probabilities of default and risk premium components. Lastly, we construct a range of economic fundamentals and assess their explanatory power in predicting future systemic default risk.

4.1. **Systemic Default Risk in the European Sovereign System**

Panel A of Fig. 3 presents the results of the bootstrapped probabilities of default for the 10 EA sovereigns. Sovereign default risk was virtually non-existent at the beginning of 2008, indicating that market participants perceived European sovereigns to be safe havens. However, sovereign PoD values began to increase steadily since the Lehman Brothers’ collapse in September 2008. We notice a major increase in the PoD for Greece in May 2010 when the average pairwise correlation during the global finance crisis was 0.50; this gradually decreased to 0.47 during the sovereign debt crisis.
EA countries and the International Monetary Fund (IMF) agreed on the first bailout package for Greece. From 2011 onwards, we observe extensive divergence in the PoD values of individual sovereigns. Such large cross-sectional variation in PoD can be attributed to the varying effects that the sovereign debt crisis had on each sovereign. For example, both Ireland and Portugal maintained similar PoD levels in early 2011, but Ireland’s PoD decreased dramatically relative to Portugal’s in the latter half of 2011. Throughout the sample period, Germany and the Netherlands maintained the lowest PoD values, followed by other core sovereigns, such as Austria and France.

Panel B of Fig. 3 illustrates the joint default risk of the European sovereign system. Joint sovereign default was considered a highly unlikely event during the global financial crisis, with risky sovereigns, such as Greece, peaking at a maximum joint probability of default of only 1% shortly after the Lehman Brothers’ collapse. As the sovereign debt crisis evolved, we begin to see rapid increases in the joint default risk of the sovereign system. More specifically, Greece and Portugal were the most likely to default with the rest of the sovereign system, reaching maximum joint probabilities of default of 6% and 4.2%, respectively, in 2012. The markets perceived Germany and the Netherlands to be the safest sovereigns, since both sovereigns barely reached joint probabilities of default of 1% throughout the majority of the sovereign debt crisis.

Panel A of Fig. 4 presents the results of the conditional joint probabilities of default for the 10 EA sovereigns, given the default of a particular sovereign. Immediately, we can see a reversal of the ordering presented in the panels of Fig. 3. For example, the CoJPoD values of Germany and the Netherlands are the highest, whereas those of Greece and Ireland are the lowest. This finding is consistent with the results obtained earlier; Germany and the Netherlands were perceived to be the safest sovereigns, thus, given a default of either sovereign, one would expect a dramatic increase in the joint default risk of the remaining sovereigns. Likewise, since investor confidence in Greece and Ireland were already low, a default in either of these sovereigns would have little influence on the joint default risk for the rest of the system.

Panel B of Fig. 4 reports the results of ∆CoJPoD for the 10 EA sovereigns, given the default of

\[11\] Greece’s PoD values plateau around 0.58 to 0.59 towards the end of our sample period because a CDS credit event occurred with respect to Greece in March 2012.
a particular sovereign. $\Delta CoJPoD$ is derived by computing the difference between the $CoJPoD$ and $JPoD$ of each sovereign. Although the ordering is extremely similar to that of Panel A, the interpretation is slightly different. As explained in Section 2.1, $\Delta CoJPoD$ measures the marginal effects of an entity’s default on the system; thus, Germany and the Netherlands have the highest marginal contribution to the systemic default risk of the sovereign system, while Greece and Ireland have the lowest. Another important aspect shown in Panel B is the ‘grouping’ effect. For example, throughout the sovereign debt crisis, the core sovereigns, consisting of Germany, Netherlands, France, Austria, and Belgium, all maintained very similar marginal contributions to systemic default risk; thus, we can group these sovereigns together to form the most systemically important collection of sovereigns. The next systemically important cluster consists of peripheral sovereigns, such as Spain, Italy, and Portugal. The last bundle contains Greece and Ireland. These groups emphasize the idea that sovereign defaults vary in degrees of severity. Therefore, in the wake of a financial crisis, the group with the highest marginal contribution to systemic default risk should receive the most attention from regulators and policymakers.

At this moment, it is worth delving into the technicalities of the $\Delta CoJPoD$ measure. As can be seen, $\Delta CoJPoD$ combines both the joint default risk dynamics of the sovereign system and individual default risk characteristics. The first component of $\Delta CoJPoD$ reflects the ratio of the joint probability of default of the sovereign system and the individual probabilities of default for each sovereign. Therefore, a sovereign with extremely low individual default risk tendencies (e.g., Germany) has a much greater conditional default risk contribution due to the inverse scaling of its marginal probability of default. Intuitively, this result is consistent with market participants balancing the severity of the default of an extremely safe sovereign against the general vulnerability of the system as a whole. Hence, when market sentiments reflect overwhelming confidence in a particular sovereign, investors will react with confounding urgency if that particular sovereign defaults. The second component of $\Delta CoJPoD$ compares the conditional joint default risk of the sovereign system with individual default risk characteristics by differencing the two. Therefore, sovereigns with high probabilities of default, such as Greece, will have minimal impact on the joint default risk of other sovereigns within the system. This
view is compatible with the idea that when the individual default risk dynamics of a particular sovereign have outgrown and outpaced the rest of the system, then its default risk spillovers due to the interdependence with the rest of the system will be marginal at best.

4.2. Systemic Default Risk in the European Banking System

One of the advantages of our CoJPoD measure is its flexibility in conditioning. Hence, we now consider the effects of sovereign defaults on the European banking system. Panel A of Fig. 5 presents the bootstrapped probabilities of default for the 26 EA banks. Each series represents the average PoD for all the banks within a particular sovereign. Consistent with our descriptive analysis in Table 5, banks residing in core sovereigns, such as Germany, France, Austria, and the Netherlands, maintained the lowest probabilities of default throughout the sample period. In contrast, Irish and Portuguese banks were perceived to be extremely risky, with investor concerns intensifying during the sovereign debt crisis as probabilities of default for Irish banks increased to values of over 30%. This result further emphasizes the large differential in investor default risk perceptions between core and peripheral sovereigns.

Panel B of Fig. 5 presents the joint probability of default of the European banking system with each of the 10 EA sovereigns. By combining the default risk dynamics of the entire banking system with the default risk characteristics of individual sovereigns, we are able to unveil important information regarding changes in investors’ joint default risk perceptions. To illustrate, during the global financial crisis, whether we include core or peripheral sovereigns in the banking system seems to be of small importance to investors, since joint probabilities of default remained relatively homogeneous for all sovereigns. However, during the sovereign debt crisis, the inclusion of risky sovereigns, such as Greece and Portugal, evokes considerable response from investors in the form of increased joint probabilities of default. This result is consistent with the idea that investors were extremely cautious of peripheral sovereigns during the sovereign debt crisis because they feared that the unsustainable fiscal conditions of Greece and Portugal could migrate into the banking sector, and thus, cause a collapse of the entire banking system. On the other hand, if we include relatively safe sovereigns such as Germany and the Netherlands in the banking system, investors show little concern (as reflected by low
joint probabilities of default), since the strong debt financing abilities of these sovereigns help soothe investor doubts.

Panel A of Fig. 6 presents the CoJPoD of the banking system, given the default of a particular sovereign. Similar to previous analyses, we witness the overwhelming systemic importance of core European sovereigns such as Germany, France, and the Netherlands. Our results strongly indicate that these three sovereigns form the pillars for both the European sovereign and banking system. As shown in Table 5, these three sovereigns also contain the largest banks within the EA, measured by both total assets and total liabilities. Such an observation is reminiscent of the highly publicized ‘too-big-to-fail’ argument often prevalent in the systemic risk literature. That is, Germany, France, and the Netherlands are perceived by investors to be so interconnected and critical to the functioning of the economy such that their default would incur severe financial losses on the European banking system. On the other end of the spectrum lies Greece; its low systemic default risk contribution throughout the entire sample period is a result of the massive downgrading from market participants due to its persistent likelihood of default combined with unmaintainable levels of government deficit.

Panel B of Fig. 6 presents the ΔCoJPoD of the banking system, given the default of a particular sovereign. For the majority of the financial crisis and throughout the sovereign debt crisis, we observe similar grouping effects as shown in Panel B of Fig. 4. That is, core sovereigns maintain the highest marginal contribution to the systemic default risk of the banking system, while peripheral sovereigns are perceived by investors to be less systemically important. While the bank ΔCoJPoD of core sovereigns tend to co-vary throughout the entire sample period, the same cannot be said for that of peripheral sovereigns. In fact, the variation in bank ΔCoJPoD of peripheral sovereigns can be segmented into three periods. From the beginning of our sample period to mid-2010, Italy, Spain, Portugal, and Ireland all maintained very similar marginal contributions to the systemic default risk of the banking system. From mid-2010 to the end of our sample period, the bank ΔCoJPoD of Italy and Spain were continuously greater than that of Portugal and Ireland. Finally, from mid-2011 onwards, we witness a major divergence in the bank ΔCoJPoD of Portugal and Ireland. The large devaluation in Ireland’s bank default risk contributions can be attributed to the worsening economic conditions at that time; Irish
banks’ debt were downgraded to junk status by Moody’s, European leaders agreed to massive cuts in the interest rates that Ireland was paying on their first bailout loan, and finally, debate circled whether the newly elected Irish government would need a second bailout package. Not surprisingly, these series of events elicited considerable backlash from investors, which resulted in a significant downturn in Ireland’s bank ∆CoJPoD.

Another observation from Panel B of Fig. 6 is that, as far as market perceptions are concerned, the effects of sovereign defaults on the European banking system were perceived to be much more potent during the sovereign debt crisis than during the financial crisis. This finding may be partly explained with reference to the ‘too-big-to-fail’ doctrine. The sovereign debt crisis was a period characterized by widespread bailout programmes and, more importantly, immense government support for large banks. Many commentators, including Federal Reserve Chairman Ben Bernanke, have argued that the ‘too-big-to-fail’ status of large banks allowed them to borrow capital at artificially low interest rates. Such actions greatly inflate the systemic risk of the banking sector in the absence of proper regulatory resolutions. Furthermore, the safety net granted to these banks generates adverse moral hazard issues (Stern et al., 2004; Mishkin, 2005). As market expectations converge towards the unlikelihood of default for these ‘too-big-to-fail’ banks, investors will have little incentive to monitor their risk-taking activities. As a direct consequence, large banks are more likely to take on greater risks and expect unequivocal government support if they fail. But the story does not end here, governments that are forced to bail out large banks experience a great amount of fiscal stress, which then translates into weaker sovereign funding. Undeniably, this very issue was one of the catalysts driving the European sovereign debt crisis. Since the majority of Europe’s largest banks are located within the core sovereigns, then it is surprise that we observe greater bank ∆CoJPoD values for core sovereigns during the sovereign debt crisis than during the global financial crisis.

4.3. Evolution of Systemic Risk in the European Banking System

We now examine the aggregate level of systemic risk in the European banking system by averaging the bank CoJPoD shown in Panel A of Fig. 6. Fig. 7 presents the time variation in the average conditional joint probability of default of the European banking system, given the
default of a particular sovereign. The most distinguishing feature of Fig. 7 is that the systemic risk of the European banking system reached historical highs of 29% during the midst of the sovereign debt crisis in late 2011. Such high levels of bank default risk were most likely prompted by widespread panic and relentless unrest as European sovereigns adopted various austerity measures in an attempt to secure further bailout packages to diffuse the pending catastrophe. Furthermore, we observe three major peaks in our systemic risk indicator during the global financial crisis, suggesting that European banks were also prone to systemic shocks originating from the United States. Indeed, Trapp & Wewel (2013) show that European banks reacted more strongly to the onset of the global financial crisis than US banks. Thus, for a closer examination, we split the evolution of the \( \text{CoJPoD} \) for the banking system into two periods. Fig. 8 presents the \( \text{CoJPoD} \) of the banking system during the global financial crisis and Fig. 9 presents the progression during the European sovereign debt crisis.

The European bank default risk was the lowest at the beginning of our sample period (Fig. 8) but began to climb rapidly 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 moved to bail out Bear Stearns. However, this episode was quickly defused due to rapid interventions by the US central bank. Such actions were felt by the European banking system, indicating strong financial spillovers from the United States. A small peak materialized on 7 July 2008, when Fannie Mae and Freddie Mac plunged on capital concerns. Although these two enterprises play a key role in the US housing market, US government intervention did not appear to affect the European banking system relative to other major default events. Following this, we see a dramatic rise in the systemic risk indicator as the European banking system clearly felt the ripple effects due to the Lehman Brothers’ collapse. The conditional joint probability of default of the banking system increased to values of around 15%, eclipsing the earlier peaks. The ensuing loss of confidence throughout the global financial markets coupled with detrimental losses for institutions that were heavily exposed to the Lehman Brothers meant that the real economy was also affected. A period of recovery followed, as the G20 Summit vowed to boost growth and prevent future crises. This pledge was short-lived, as the \( \text{CoJPoD} \) peaked during the financial crisis to values in the range of 17% on 10 March 2009, coinciding with the
Dow Jones Industrial Average slumping to an all-time low. Our results indicate 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 the vulnerabilities in the global financial system. Indeed, the significant rise in our $CoIPoD$ measure shows that European banks were not spared from the aftereffects 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. This outcome was largely due to the adoption of policies that intended to stimulate the economy, provide liquidity, enhance bank regulation, and reinforce international cooperation. Following such actions, our systemic risk indicator began to decline, indicating a period of prolonged recovery.

The evolution of $CoIPoD$ throughout the sovereign debt crisis was mostly a result of credit events that spawned within the EA (Fig. 9) rather than external shocks from the United States. The onset of the sovereign debt crisis saw our systemic risk indicator increase at a rapid rate, with it peaking on 2 May 2010, when Greece signed a €110 billion loan package with the European Union and IMF. The conditional joint probability of default of the European banking system continued to increase steadily as subsequent bailout programmes were also provided to Ireland in December 2010. In late 2011, our systemic risk indicator reached unprecedented levels as market participants feared the possibility of cascade effects. Indeed, the G20 Summit on 14 October 2011 raised concerns regarding the possible financial contagion of a Greek default spreading to core sovereigns and accelerating the fiscal distress of peripheral sovereigns. European leaders also acknowledged heightened tensions in the European financial markets as unemployment levels soared into unacceptable regions for advanced economies. In an attempt to reverse the weakening rate of recovery, European leaders vowed to make fundamental reforms through robust economic governance, increasing financial resilience against volatile capital flows, and the formation of financial firewalls to contain spillover effects. Despite these measures, the conditional joint probability of default of the European banking system reached an all-time high shortly before the implementation of the ECB’s three-year long-term refinancing operations on 21 December 2011. Immediately following the agreement on the second
financial aid package from the European Financial Stability Facility to Greece on 21 February 2012, we witness another small build-up in \( CoJPoD \), which peaked on 27 June 2012, when both Spain and Cyprus requested financial support from other EA members. Ultimately, the financial assistance granted by the Eurogroup to Spain’s banking sector on 20 July 2012 marked the beginning of a 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.

As mentioned in Section 1, Black et al. (2013) utilize the DIP to examine the level of systemic risk in the European banking system. For comparisons with \( CoJPoD \), Panel B of Figure 7 presents the evolution of the DIP, assuming at least 10% of total liabilities in the banking system are in default. We focus on the period 1 January 2008 to 28 February 2013. Immediately, it can be seen that the time variations in the DIP and bank \( CoJPoD \) are very similar. Most notably, during the financial crisis, the evolution of both systemic risk measures are characterized by three major peaks: the Bear Stearns acquisition, the collapse of Lehman Brothers, and the Dow Jones Industrial Average reaching an all-time low. However, the interpretation is quite different, for example, at the height of the financial crisis on 10 March 2009, the DIP indicates a premium rate of 1% is needed to cover the European banking system’s exposure to defaulting liabilities. On the other hand, \( CoJPoD \) reveals that the average conditional joint probability of default of the European banking system is 17%, given the default of each of the 10 EA sovereigns. Thus, the \( CoJPoD \) can be considered as a probabilistic alternative to the DIP. From 2010 onwards, both the DIP and \( CoJPoD \) experience similar co-movements, indicating that both measures appear to be extremely sensitive to changes in systemic risk during the sovereign debt crisis. Indeed, both measures document the systemic default risk of the European banking system reaching an all-time high in late 2011. Specifically, the DIP documents a premium rate of well over 2% is needed to cover financial distress in the banking system, while \( CoJPoD \) indicates that the conditional joint default risk of the banking system is 29%. Overall, it can be seen that both the DIP and \( CoJPoD \) provide complementary information with regards to the evolution of systemic risk in the European banking system.
4.4. **Determinants of Systemic Risk Indicator**

In this section, we examine which fundamental credit risk variables explain the variation in our \( \text{CoJPoD} \) measure. Table 6 investigates the determinants of \( \text{CoJPoD} \) for both the sovereign and banking system using ordinary least squares (OLS) regression. To control for bias caused by serial correlation, we use heteroskedasticity and autocorrelation consistent Newey-West standard errors (Petersen, 2009). As can be seen from Panel A, marginal bank probability of default (\( \text{Bank PoD} \)) is a principal factor in explaining conditional bank joint default risk, since it alone explains 98% of the variation in bank \( \text{CoJPoD} \) (column (1)). Its economic effect is also significant, since a 1% increase in individual bank probability of default increases the conditional joint default risk of the banking system by 2.59%, on average. We also consider the effect of bank equity correlations (\( \text{Bank Corr} \)) on the systemic default risk of the European banking system. As mentioned in Section 3, pairwise correlations computed from equity returns is a good indicator for the level of interdependence between banks during times of crisis. Hence, we expect a positive relationship between bank correlation and \( \text{CoJPoD} \). On its own, bank correlation only explains 16% of the total variation in bank \( \text{CoJPoD} \); it also has an unexpected negative sign in columns (2) and (3), most likely due to omitted variable bias. When we include all explanatory variables in column (4), bank correlation has the expected positive sign and is also significant at the 5% level. This result suggests that the degree of interconnectedness between banks is also a main driver of conditional joint default risk in the European banking system.

We include two new variables in column (4): the standard deviation in the bank \( \text{PoD} \) (\( \text{Bank PoD Stdev} \)) and the standard deviation in bank correlations (\( \text{Bank Corr Stdev} \)). Using \( \text{Bank PoD Stdev} \), we attempt to examine the other popular proposition of ‘too-many-to-fail’ (as opposed to ‘too-big-to-fail’) often prevalent in the financial stability literature. This term was first coined by Yorulmazer & Acharya (2007) to describe the ex-ante herding behaviour of banks as regulators found it ex-post optimal to bail out the majority of the banks, given the default of a large number of banks. The authors argue that in many ‘too-big-to-fail’ situations, there exists an implicit ‘too-many-to-fail’ problem that may be more relevant. Zhou (2010) argues that the systemic nature of a financial institution should be examined in conjunction with its co-distress
risk with other institutions. Therefore, it is highly possible that the ‘too-many-to-fail’ argument is more pertinent during a financial crisis than the ‘too-big-to-fail’ argument. As can seen immediately from column (4), the standard deviation in bank \( PoD \) is statistically significant at the 1% level. More specifically, a 1% increase in the heterogeneity of bank \( PoD \) decreases the conditional joint default risk of the European banking system by 0.70%, on average. This result shows that European regulators find it optimal to bail out a large number of banks only when sector-wide banking difficulties becomes apparent. Likewise, if only a small group of banks default, indicating minimal losses, then regulators may refrain from intervention and rely on the private sector to liquidate these failing banks. Overall, our findings provide evidence for the existence of the ‘too-many-to-fail’ problem and hint that both the size and number of banks defaulting play an important role in determining the extent of sovereign defaults on the European banking system. Our second variable, \( Bank \ Corr \ Stdev \), examines whether uncertainty in bank interdependencies affect the conditional joint default risk of the banking system. Column (4) shows that \( Bank \ Corr \ Stdev \) is statistically significant at the 1% level and that a 1% increase in the standard deviation of bank correlations increases the conditional joint probability of default of the banking system by 0.11%, on average. This result indicates that the conditional joint probability of default of the European banking system is not only influenced by the degree of interdependence between banks but also largely determined by the uncertainty in the degree of interdependence.

In Panel B of Table 6, our dependent variable is \( Sovereign \ CoJPoD \). As can be seen immediately from all four columns, marginal sovereign probability of default (\( Sovereign \ PoD \)) is the most dominant factor in explaining sovereign conditional joint default risk, explaining 85% of the variation alone (column (1)) and 86% of the variation when combined with sovereign correlations (\( Sovereign \ Corr \)) (column (3)).\(^{12}\) Its economic significance is the strongest in column (4), where a 1% increase in individual sovereign probability of default increases the conditional joint default risk of the rest of the sovereign system by 4.35%, on average. Although sovereign correlation maintains a positive coefficient across all columns, it is barely significant in columns (2) and (4), indicating that the degree of interdependence between sovereigns is of

\(^{12}\)Sovereign correlations are based on daily arithmetic stock market returns of the main stock market index of each sovereign.
minimal concern once individual sovereign default risk characteristics are taken into consideration. Furthermore, column (4) shows that uncertainty in the level of sovereign interdependencies (*Sovereign Corr Stdev*) does not seem to significantly affect the conditional joint default risk of the sovereign system. This result shows that the numerous bailout packages provided to peripheral sovereigns coupled with the implementation of various austerity measures have been successful in defusing financial contagion risks. In contrast, heterogeneity in sovereign *PoD* (*Sovereign PoD Stdev*) has a significant negative effect on sovereign *CoJPoD* (column (4)), providing evidence for the presence of the ‘too-many-to-fail’ problem in a sovereign context. This result is consistent with Brown & Dinc (2011), who find that the ‘too-many-to-fail’ effect is more prevalent for sovereigns that have larger government deficits. Indeed, widespread sovereign defaults incur devastating losses on both the financial markets and the real economy, thus it becomes optimal for European regulators to bail out a ‘herd’ of distressed sovereigns during crises that are systemic in nature.

4.5. **Decomposition of Systemic Risk Indicator**

The European sovereign debt crisis was a full-fledged economic crisis that not only affected the financial markets but also spilled over to the real economy. These effects placed immense pressure on the European banking system and also generated substantial downward revisions in the credit qualities of European banks. In addition, the widespread loss of confidence significantly reduced consumer demand, causing risk premiums to rise considerably. As mentioned in Section 2.4, our *CoJPoD* measure encompasses both physical probabilities of default and risk premiums. Therefore, by decomposing our systemic risk indicator into each component, we are able to ascertain how much of its variation is driven by the pure credit qualities of European banks and how much is steered by changes in market risk perceptions.

Table 7 presents the results of the decomposition for both sovereign and bank *CoJPoD*. As can be seen from Panel A, the sovereign risk premium (*SRP*) alone explains 90% of the variation in bank *CoJPoD* (column (4)) and remains statistically significant at the 1% level in both univariate and multivariate regressions. Its magnitude is also astounding; a 1% increase in the sovereign risk premium increases the conditional joint default risk of the banking system by
7.18%, on average (column (5)). Therefore, the sovereign risk premium appears to be the dominant factor in driving the CoJPoD of the European banking system. As for the other two risk premium components, the default risk premium (DRP) explains only 4.8% of the total systemic risk variation (column (2)), while the liquidity risk premium (LRP) has no explanatory power on its own (column (3)). Physical probability of default, as proxied by DTD, appears to play an important role in determining bank CoJPoD. It explains 36% of the total variation by itself (column (1)) but reduces in significance and magnitude once the risk premium components are included in the multivariate regression (column (5)). Nevertheless, the coefficient on DTD maintains the expected negative sign, indicating that a one-unit increase in DTD decreases the conditional joint probability of default of the banking system by 3.46%, on average (column (5)). This finding demonstrates that the physical stress placed on Europe’s banking system has slowly but surely weakened its economic fundamentals.

Our results are also consistent with the credit events that unfolded during the sovereign debt crisis. In late 2011, French banks were heavily affected by liquidity shortages and unfavourable funding conditions. Major commentators such as PIMCO’s CEO Mohamed El-Erian believed that the collapse of French banks could plunge Europe into a full-blown banking crisis. Furthermore, French banks suffered greatly from decreasing levels of capital and reduced lending from short-term investors. Such deterioration in traditional banking operations led to the downgrade in the debt of major French banks such BNP Paribas, Société Générale, and Crédit Agricole. Therefore, it is no surprise that changes in physical probabilities of default were the root cause for much of the banking problems experienced by core European banks. On the other end, Italian and Spanish banks were mostly affected by increases in risk premiums rather than credit issues. In the case of Spain, various bank bailouts coupled with unsustainable levels of government deficit led to a substantial downgrading in its credit rating. As such, increases in the spread between average Spanish and Italian bond yields and German yields became the main driving force behind increases in systemic risk.

Panel B of Table 7 examines the decomposition of sovereign CoJPoD. Qualitatively our results are very similar to those of Panel A. Again, the sovereign risk premium is the most important factor, since it alone explains 79% of the total variation in sovereign CoJPoD (column
much more than the default risk premium (6.9%) (column (2)) and the insignificant liquidity risk premium (column (3)). In the multivariate regression (column (5)), on average, a 1% increase in the sovereign risk premium increases the conditional joint default risk of the sovereign system by 8.09%, indicating that the sovereign risk premium maintains a strong economic effect even in the presence of other risk premium components. In contrast to Panel A, the liquidity risk premium has been driven to insignificance once all other components are included in the regression (column (5)). This finding suggests that the European sovereign system is less concerned with the liquidity shortage problems of the banking sector once other risk premiums are taken into consideration. Physical probability of default continues to plague the European economy, since it alone explains 36% of the variation in sovereign CoJPoD (column (1)) and appears to have a greater effect on the sovereign system relative to the banking sector. Specifically, on average, a one-unit increase in DTD decreases the conditional joint default risk of the sovereign system by 12.72% (column (5)). This result is consistent with the massive downgrading of sovereign creditworthiness during the heart of the sovereign debt crisis. The inability of peripheral sovereigns to cushion against unexpected shortfalls combined with negative economic outlook resulted in a severe deterioration of the macroeconomic performance of the entire European sovereign system. Inevitably, objective default risk has risen extensively as the European sovereign debt crisis evolved into a real economic recession.

4.6. Predictive Power of Economic Fundamentals

In the previous sections, we analyzed the evolution of bank and sovereign CoJPoD at both the aggregate and individual levels. Our results revealed a strong correlation between CoJPoD and major credit events throughout the global financial crisis and the sovereign debt crisis. In particular, we have shown that our CoJPoD measure is sensitive to changes in market risk perceptions and movements in credit quality. In this section, we proceed to examine a range of economic fundamentals and assess their forecasting power. Table 8 presents a set of panel OLS regressions where we use CoJPoD\textsubscript{(sov system|sov)} (columns (1) to (2)), CoJPoD\textsubscript{(sov|sov system)} (columns (3) to (4)), CoJPoD\textsubscript{(bank system|sov)} (columns (5) to (6)) and CoJPoD\textsubscript{(sov|bank system)} (columns (7) to (8)) as the dependent variables. All independent variables except for Term
Spread and VSTOXX are lagged by one year. All regressions include sovereign fixed effects and employ White heteroskedasticity-consistent standard errors clustered by sovereign. The sample period is from 1 January 2008 to 28 February 2013 and each regression is run on a monthly basis.\textsuperscript{13} For ease of interpretation, all independent variables except for Log GDP are measured in \%. 

In our regression analyses, VSTOXX and Term Spread serve as control variables that attempt to capture the general economic conditions of the EA. The first variable, VSTOXX, controls for the regional uncertainty of the EA by using the 24-month VSTOXX volatility index. Prior literature has documented significant positive relationships between the value of the VIX\textsuperscript{14} volatility index and the spreads of financial instruments such as CDS contracts and sovereign bonds (see Berndt et al. (2005), Collin-Dufresne et al. (2001) and Schaefer & Strebulaev (2008)). Thus, it is reasonable to assume the VSTOXX index reflects the market perceptions of short-term volatility in Europe. Intuitively, increases in the VSTOXX index signifies uncertainty regarding the strength of economic fundamentals of European sovereigns; hence, we predict a positive relationship between regional volatility and conditional joint default risk. We confirm our conjecture, since the coefficient on VSTOXX is positive and significant at the 1\% level in all columns. This result indicates that contemporaneous increases in the VSTOXX index are significantly associated with higher conditional joint probabilities of default in the European sovereign and banking system. Our second control variable, Term Spread, accounts for the term structure of interest rates in the EA. Following Duffee (1998), we proxy for the term structure by using the difference between the ten-year and three-month AAA EA bond yields. General economic theory predicts that the term spread may have confounding effects on our CoIPoD measure. Increases in the slope of the term spread may indicate expectations of improvement in the state of the economy but could also reflect tightening monetary policy in order to dampen inflation rates. The coefficient on the term spread variable is significantly positive in most of the specifications suggesting that the latter effect may be more dominant in our sample.

In columns (1) and (2) of Table 8, we use the conditional joint probability of default of the

\textsuperscript{13}We apply cubic spline interpolation to transform yearly and quarterly data to monthly frequency.

\textsuperscript{14}The VIX index is a measure of the implied volatility of Standard & Poor's 500 index options.
sovereign system, given the default of a particular sovereign, as the dependent variable. The independent variables are the economic fundamentals of the defaulting sovereign. Theoretically, we predict that if the defaulting sovereign had stable economic prospects, signalled by positive stock market returns, then its default should increase the joint default risk of the remaining sovereigns left in the system (Longstaff et al., 2011). In line with our expectations, the coefficients on the six-month rolling stock market returns and one-month average returns are all positive and significant at the 1% level. This finding suggests that changes in the local business climate of European sovereigns have significant predictive power one year prior to increases in the conditional joint default risk of the sovereign system. From a different perspective, we expect sovereigns with positive economic outlook to better resist against a sovereign system default; we examine this issue in columns (3) and (4). Although the coefficient on the six-month rolling stock market return is insignificant, we find a statistically significant negative coefficient on the one-month average return variable. This result provides some evidence that sovereigns with stronger economic performance are better able to cope with a default of the sovereign system.

We also account for the volatility of a sovereign’s economic performance. Prior literature indicates that stock market volatility plays an important role in determining CDS spreads during financial crises (Alexander & Kaeck, 2008). We construct two measures to proxy for volatility, the first being the standard deviation of the six-month rolling stock market returns and the second being the monthly average standard deviations of stock market returns. In times of financial crises, high volatility in the stock market reflects uncertainty about the prospects of the economy to generate profitable opportunities. In a sovereign context, this situation translates to unpredictability in how a government manages its income and uses it to service their debt interest payments. Therefore, we predict that the conditional joint default risk of the sovereign system will decrease if the defaulting sovereign has high stock market volatility. We find evidence for this prediction in column (2) of Table 8, since the coefficient on the monthly average standard deviations of stock market returns is negative and significant at the 1% level. This result also indicates that volatility in economic prospects is a key predictor for future systemic default risk in the sovereign system. Using the same argument, we expect sovereigns with un-
certain prospects to be more sensitive to the default of other sovereigns. However, we do not find any evidence of this, since the coefficients on both volatility measures in columns (3) and (4) are statistically insignificant.

Next, we examine whether the size of a sovereign influences systemic default risk. To proxy for size, we use the natural logarithm of the sovereign’s real GDP based on year 2000 euro prices. Prior literature shows that the size of an economy is a significant factor in determining its probability of default; for example, Hassan (2012) shows that larger sovereigns have significantly lower bond yields and generally have lower probabilities of default. Thus, we predict that the conditional joint default risk of the sovereign system will increase, given the default of a large sovereign. Columns (1) and (2) of Table 8 support this conjecture, since the coefficients on Log GDP are positive and statistically significant at the 1% level in both specifications. Its economic effect is also startling; on average, a 1% increase in GDP predicates a 0.91% (column (1)) and 0.84% (column (2)) increase in the one-year-ahead conditional joint default of the sovereign system. Equivalently, we expect larger sovereigns to be more resilient to the defaults of other sovereigns in the system. Indeed, Pan & Singleton (2008) note that CDS traders consider country size to be an extremely important factor when determining recovery time during a financial crisis. Thus, larger sovereigns should experience lower default probabilities, given the default of the sovereign system. Columns (3) and (4) confirm this prediction, since the coefficients on Log GDP are significantly negative at the 1% level, demonstrating that the ability of larger sovereigns to buffer against external shocks has significant power in predicting the future systemic default risk of individual sovereigns. Our results regarding the dominant effect of sovereign size provides more concrete evidence for the existence of the ‘too-big-to-fail’ theory. Precisely, we have shown that the default of large sovereigns inflict disastrous ripple effects throughout the sovereign system and large sovereigns that are ingrained within the economy are less likely to default, possibly due to the assistance of third parties.

To control for a sovereign’s debt obligations, we compare the sovereign’s total government debt relative to its GDP (Debt/GDP). As mentioned in our prior analyses, the European sovereign debt crisis is characterized by large amounts of government debt due to various bailout schemes and stimulus packages. Numerous papers have found that the debt-to-GDP ratio is priced in
sovereign debt instruments (Edwards, 1986; Min, 1998; Hilscher & Nosbusch, 2010). Therefore, it is interesting to see whether market participants take into consideration the debt position of a sovereign when determining systemic default risk. We hypothesize that the default of a sovereign with high levels of government debt should increase the joint default risk of the sovereign system. By the same token, we predict higher government indebtedness to be associated with greater probabilities of default, given the default of the sovereign system. In accordance with our expectations, we find that the one-year-ahead conditional joint probability of default of the sovereign system increases when the defaulting sovereign has high levels of government debt (columns (1) and (2) of Table 8). The reverse effect is much less pronounced, since the coefficient on the debt-to-GDP ratio is barely significant in columns (3) and (4).

Finally, we consider the effects of the reserve-to-debt (Reserve/Debt) ratio on sovereign default risk. Since we are more interested in the liquidity positions of sovereigns, we exclude gold from total reserves. Increasing a sovereign’s reserves should serve as a liquidity buffer against unexpected shocks. Hence, market participants should perceive sovereigns with higher reserves (relative to debt) to be a safer place in which to invest. Therefore, the default of a sovereign with a high reserve-to-debt ratio indicates instability throughout the entire sovereign system. This situation should lead to an increase in the joint default risk for the remaining sovereigns in the system. Columns (1) and (2) of Table 8 confirm this presumption and show that improvements in the liquidity positions of defaulting sovereigns can significantly predict increases in the one-year-ahead conditional joint default risk of the sovereign system. According to a similar argument, sovereigns with a large reserve should be able to cushion against disturbances in income flow. However, an overarching theme during the European sovereign debt crisis was lax government spending and excessive risk taking. Therefore, sovereigns with extra insurance against potential shortfalls are more likely to take on unnecessary risks (Perotti et al., 2011). We find evidence for such behaviour in columns (3) and (4), since the coefficient on the reserve-to-debt ratio is positive and significant at the 5% level. This finding implies that sovereigns with high levels of reserves are more likely to default in the future, possibly due to their participation in riskier activities.

In columns (5) to (8) of Table 8, we apply the same set of regressions but replace the sovereign
system with the banking system. Our strategy remains the same in determining the predictive ability of economic fundamentals on the one-year-ahead $CoJPoD$ involving the banking system. Similar to columns (2) and (4), we find that defaulting sovereigns with strong local business climates are more likely to increase the one-year-ahead $CoJPoD$ of the banking system (column (6)), whereas improvements in the local economic conditions are more likely to decrease the future default risk of a sovereign, given the default of the banking system (column (8)). We also obtain comparable results regarding the volatility of a sovereign’s economic performance. More specifically, we find evidence for decreases in the one-year-ahead conditional joint default risk of the banking system, given the default of a sovereign with uncertain economic prospects, as shown by the negative and significant coefficient on the market volatility variable in column (6). In line with the findings of column (4), volatile economic performance does not seem to have any significant explanatory power in predicting future sovereign default risk, given the default of the banking system, as shown by the insignificant coefficient on the volatility measure in column (8).

As expected, the ‘too-big-to-fail’ phenomenon is again prominent in our results. The positive and significant coefficients on $\log GDP$ in columns (5) and (6) of Table 8 indicate that the default of a large sovereign is detrimental to the banking system. Likewise, the significantly negative coefficients on $\log GDP$ in columns (7) and (8) signify that large sovereigns are highly resilient to the default of the European banking system. In accordance with earlier results, the default of a sovereign with large debt obligations, as proxied by the debt-to-GDP ratio, is associated with future increases in the default risk of the banking system (columns (5) and (6)). In contrast, a sovereign’s debt position does not seem to affect its future probability of default, given the default of the banking system, as shown by the insignificant coefficients on the debt-to-GDP ratio in columns (7) and (8). The reserve-to-debt ratio is positive and significant in columns (5) and (6), suggesting that the default of a sovereign with large reserves is likely to escalate the distress in the banking system, thereby increasing the system’s one-year-ahead conditional joint default risk. The ratio maintains a positive and significant coefficient in columns (7) and (8), indicating that sovereigns with greater reserves are perhaps more likely to take on unnecessary risks, thereby increasing their future probability of default, given the
default of the banking system.

5. Conclusion

In this paper, we construct a conditional measure of systemic risk, \( CoJPoD \), to quantify the effects of a sovereign default on the European sovereign and banking system. We incorporate individual default risk characteristics combined with joint default risk dynamics to create a measure that is applicable in a true multivariate setting. In addition, we fully exploit the conditional flexibility in our systemic risk indicator by investigating systemic risk in both the sovereign and banking system. Finally, we ensure that our systemic risk measure not only captures market perceptions regarding default risk but also is sensitive to any changes in objective default rates.

Our results indicate that Germany and the Netherlands have the highest perceived marginal contribution to the systemic default risk of the European sovereign and banking system, given their own default. On the other hand, peripheral sovereigns such as Greece, Ireland, and Portugal form the least systemically important group of sovereigns. Furthermore, at both the individual and aggregate level, the evolution of our systemic risk indicator coincides with the occurrence of major credit events throughout the global financial crisis and the sovereign debt crisis. In particular, we show that the conditional joint default risk of the European banking system reached historical highs of 29% during the heart of the sovereign debt crisis, in late 2011. Although we attribute the majority of this heightened risk to increases in the sovereign risk premium, we also document a steady increase in underlying physical probabilities of default, suggesting that the heightened risk was not only due to changes in market risk sentiments but also a result of the weakening credit quality of European banks.

With respect to the main determinants of conditional joint default risk, we show that individual default risk characteristics of sovereigns and banks are the main driving force behind increases in the conditional joint probabilities of default for the sovereign and banking system. Furthermore, we demonstrate that the level of interdependence between banks and uncertainty in the degree of interdependence amplify the systemic default risk of the European banking system.
We also document the existence of the ‘too-many-to-fail’ phenomenon, hinting that both the size of defaults and the number of defaults play an important role in determining the full scope of the European sovereign debt crisis. From a policy perspective, we show that European regulators find it optimal to bail out a large number of banks or sovereigns when the economic costs of default overshadow the size of bailout packages. However, to come up with more meaningful recommendations from a regulatory point of view, CoJPoD needs to be modified to account for the expected losses, given a default. For example, since CoJPoD provides the conditional joint probability of default and DIP measures the insurance premium needed to cover defaults, future research could work on synergizing these two measures to come up with an estimate of the expected losses in the case of a joint default. The resulting estimate can be weighed against the costs of bailout packages to determine the most optimal regulatory decisions.

With regards to the predictive power of economic fundamentals, we find that a sovereign’s economic performance, uncertainty in economic prospects, size, debt obligations, and liquidity buffers all have substantial predictive ability in assessing changes in the one-year-ahead conditional joint default risk of the European sovereign and banking system. In particular, we document that sovereign size is, by far, the most dominant factor in predicting future changes in conditional joint probabilities of default. Consequently, we show that the ‘too-big-to-fail’ doctrine is prevalent throughout our sample period, indicating that large sovereigns are often the recipients of beneficial policies to prevent a systemic collapse of the European sovereign system. Furthermore, our analyses lead to important policy implications, since it identifies the possible transmission channels for future systemic default risk, hence providing important insights for European regulators when developing appropriate measures to defuse contagion risks.
References


A. Proofs

A.1. Bootstrapping Probabilities of Default from CDS Spreads

Assume we have a \( N \) CDS contracts on the same reference obligor with maturities \( T_1 < T_2 < \cdots < T_N \) and par spreads \( s_1, s_2, \cdots, s_N \), where \( s_i \geq 0 \) for \( i = 1, 2, \cdots, N \). We seek to bootstrap a default probability curve such that when it is used to value the CDS contracts, we obtain the same par spreads.

Define \( \tau \) to be the time at which the reference obligor defaults and let \( \text{PoD}_{\text{cum}}(t) = P(\tau < t) \) denote the cumulative probability of default of the reference obligor before time \( t \). Then denote the probability that the reference entity ‘survives’ until time \( t \) as \( S(t) = 1 - \text{PoD}_{\text{cum}}(t) \), often called the survival probability. Given \( \text{PoD}_{\text{cum}}(t) = P(\tau < t) \), we define the default density function, \( q(t) \) as:

\[
\text{PoD}_{\text{cum}}(t) = \int_0^t q(v) dv \quad \text{where } q(t) \geq 0 \text{ for all } t \geq 0
\]

For any \( \{v|v \in (0,t)\} \), we have:

\[
\text{PoD}_{\text{cum}}(t) = \text{PoD}_{\text{cum}}(v) + [\text{PoD}_{\text{cum}}(t) - \text{PoD}_{\text{cum}}(v)]
= \text{PoD}_{\text{cum}}(v) + \int_v^t q(s) ds
\]

Define the hazard rate function \( h(t) \) such that it satisfies:

\[
S(t) = \exp \left( - \int_0^t h(v) dv \right)
\]

Therefore,

\[
\int_v^t q(s) ds = \text{PoD}_{\text{cum}}(t) - \text{PoD}_{\text{cum}}(v) = S(v) - S(v) \exp \left( - \int_v^t h(s) ds \right)
\]

We assume that the par value in the case of default is $1 with a constant rate of recovery, denoted as \( R \). Following Hull & White (2000), we also assume independence between \( \tau, R \) and discount factors, denoted as \( F(t) \). Then the present value of the payoff (‘payoff leg’) of a CDS
contract with maturity $T$ is given by:

$$V_{\text{payoff}} = (1 - R) \sum_{j=1}^{n} F(t_j) \left[ PoD_{\text{cum}}(t_j) - PoD_{\text{cum}}(t_{j-1}) \right]$$  \hspace{1cm} (A.3)$$

where $0 < t_1 < t_2 < \cdots < t_n$ denote the premium coupon payment dates.

Assuming that all accrued premiums are paid at the beginning of the next coupon payment date, then the present value of premium coupon payments (‘premium leg’) is given by:

$$V_{\text{premium}} = s \sum_{j=1}^{n} F(t_j) \delta_j \left[ 1 - \alpha (PoD_{\text{cum}}(t_j) - PoD_{\text{cum}}(t_{j-1})) \right] / 2$$  \hspace{1cm} (A.4)$$

where $\alpha$ takes on the value of unity if accrued premium is paid after the default of the reference obligor, $\delta_j = t_j - t_{j-1}$, and $s$ denotes the spread of the CDS contract.

To find the risk-neutral par spread of the CDS contract, we assume it generates a net present value of zero, hence:

$$V_{\text{payoff}} = V_{\text{premium}}$$

$$s_{\text{par}} = \frac{(1 - R) \sum_{j=1}^{n} F(t_j) \left[ PoD_{\text{cum}}(t_j) - PoD_{\text{cum}}(t_{j-1}) \right]}{\sum_{j=1}^{n} F(t_j) \delta_j \left[ 1 - \alpha (PoD_{\text{cum}}(t_j) - PoD_{\text{cum}}(t_{j-1})) \right] / 2}$$  \hspace{1cm} (A.5)$$

We construct a default probability curve by assuming a constant (piecewise) hazard rate function. This implies $[T_1, T_N] = [0, T_1] \cup [T_1, T_2] \cup \cdots \cup [T_{N-1}, T_N]$, thus we can partition the default probability curve on the interval $T_1 < T_2 < \cdots < T_N$ into $N$ subintervals. We begin with the first subinterval $[0, T_1]$ and use Eqn. A.2 combined with Eqns. A.3 and A.4 to numerically solve for the constant hazard rate function. We transform the hazard rate function into a default probability curve for the interval $[0, T_1]$ via Eqn. A.2. Continuing this iterative process until $T_N$ will produce a continuous default probability curve from $[0, T_N]$. Given that we choose a horizon of 5 years, we annualize the 5-year cumulative probabilities of default by using:

$$PoD_{\text{annual}}(t) = 1 - (1 - PoD_{\text{cum}}(t))^{1/5}$$
A.2. Framework for the Consistent Information Multivariate Density Optimization (CIMDO)

Methodology

We assume that there are \( n \) entities in the system where \( X_1, X_2, \cdots, X_n \) denotes the random variables corresponding to the natural log assets of institution \( I_1, I_2, \cdots, I_n \), respectively. We define the Kullback-Leibler objective function as:

\[
C(p, q) = \int \cdots \int p(x_1, x_2, \cdots, x_n) \ln \left[ \frac{p(x_1, x_2, \cdots, x_n)}{q(x_1, x_2, \cdots, x_n)} \right] dx_1 \cdots dx_{n-1} dx_n \tag{A.6}
\]

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

We minimize the functional in Eqn. A.6 with respect to \( p \) subject to the following moment consistency constraints:\(^{15}\)

\[
\int \cdots \int p(x_1, x_2, \cdots, x_n) \chi_{[X^I_d, \infty)} d x_1 \cdots d x_{n-1} d x_n = PoD_{I_1}
\]

\[
\int \cdots \int p(x_1, x_2, \cdots, x_n) \chi_{[X^I_d, \infty)} d x_1 \cdots d x_{n-1} d x_n = PoD_{I_2}
\]

\[\vdots\]

\[
\int \cdots \int p(x_1, x_2, \cdots, x_n) \chi_{[X^I_d, \infty)} d x_1 \cdots d x_{n-1} d x_n = PoD_{I_n}
\]

\[
\int \cdots \int p(x_1, x_2, \cdots, x_n) d x_1 \cdots d x_{n-1} d x_n = 1
\]

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 \( i = 1, 2, \cdots, n \), we define \( \chi_{[X^I_d, \infty)} \) as:

\[
\chi_{[X^I_d, \infty)} = \begin{cases} 
1 & \text{if } X_i \geq X^I_d \\
0 & \text{if } X_i < X^I_d
\end{cases}
\]

The corresponding Lagrangian is defined as:

\[
L(p, q) = \int \cdots \int p(x_1, x_2, \cdots, x_n) \ln(p(x_1, x_2, \cdots, x_n)) dx_1 \cdots dx_{n-1} dx_n
\]

\[- \int \cdots \int p(x_1, x_2, \cdots, x_n) \ln(q(x_1, x_2, \cdots, x_n)) dx_1 \cdots dx_{n-1} dx_n
\]

\(^{15}\)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.
+ λ₁ \left[ \int \cdots \int p(x_1, x_2, \ldots, x_n) \chi_{[X_{d_1}^n, \infty)} dx_1 \cdots dx_{n-1} dx_n - PoD_{I_1} \right] \\
+ λ₂ \left[ \int \cdots \int p(x_1, x_2, \ldots, x_n) \chi_{[X_{d_2}^n, \infty)} dx_1 \cdots dx_{n-1} dx_n - PoD_{I_2} \right] \\
+ \ldots \\
+ λₙ \left[ \int \cdots \int p(x_1, x_2, \ldots, x_n) \chi_{[X_{d_n}^n, \infty)} dx_1 \cdots dx_{n-1} dx_n - PoD_{Iₙ} \right] \\
+ \mu \left[ \int \cdots \int p(x_1, x_2, \ldots, x_n) dx_1 \cdots dx_{n-1} dx_n - 1 \right]

where λᵢ for i = 1, 2, ···, n denotes the Lagrange multipliers for the n moment consistency constraints and µ is the Lagrange multiplier for the unity constraint.

We can simplify the Lagrangian to:

\[ L(p, q) = \int \cdots \int p(x_1, x_2, \ldots, x_n) \left[ \ln(p(x_1, x_2, \ldots, x_n)) - \ln(q(x_1, x_2, \ldots, x_n)) \right. \]
\[ + \sum_{i=1}^{n} λ_i \chi_{[X_{d_i}^n, \infty)} + \mu \left] dx_1 \cdots dx_{n-1} dx_n - \sum_{i=1}^{n} λ_i PoD_{I_i} - \mu \right. \]

To minimize the functional \( L(p, q) \) with respect to \( p \), we define:

\[ F(p) = p(x_1, x_2, \ldots, x_n) \left[ \ln(p(x_1, x_2, \ldots, x_n)) - \ln(q(x_1, x_2, \ldots, x_n)) + \sum_{i=1}^{n} λ_i \chi_{[X_{d_i}^n, \infty)} + \mu \right] \]

Applying the multivariate Euler-Lagrange equation on \( F(p) \) yields:

\[ \ln(p(x_1, x_2, \ldots, x_n)) - \ln(q(x_1, x_2, \ldots, x_n)) + \sum_{i=1}^{n} λ_i \chi_{[X_{d_i}^n, \infty)} + \mu + 1 = 0 \]

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

\[ p(\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_n) = q(x_1, x_2, \ldots, x_n) \exp \left\{ - \left[ 1 + \hat{\mu} + \sum_{i=1}^{n} \hat{λ}_i \chi_{[X_{d_i}^n, \infty)} \right] \right\} \quad \text{(A.7)} \]

where \( \hat{λ}_1, \hat{λ}_2, \ldots, \hat{μ} \) denote the consistent estimators of \( λ_1, λ_2, \ldots, λ_μ \), respectively.
A.3. The Generalized Cross Entropy (GCE) Method

In order to dynamically update the posterior distribution, we need to solve for the Lagrange multipliers in Eqn. A.7 on a daily basis. We provide a solution to solve for consistent estimators of the Lagrange multipliers by using the Generalized Cross Entropy (GCE) method. Under the Cross Entropy Postulate, we minimize the Csiszar measure of cross-entropy between the prior $q$ and the posterior $p$ as follows:

$$\min_{p \in \mathcal{P}} D(p \to q) = \int_{\zeta} q(x) \psi \left( \frac{p(x)}{q(x)} \right) dx$$  \hspace{1cm} (A.8)

where $x = [x_1, x_2, \cdots, x_n]^T \in \zeta \subset \mathbb{R}^n$ and $\mathcal{P} = \left\{ p : \int p(x) dx = 1, p(x) \geq 0, \forall x \in \zeta \right\}$. Additionally, $\psi$ 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 Eqn. A.8 is subject to the generalized moment constraint set, $\Omega$:

$$\mathbb{E}_p[K_i(X)] = \int_{\zeta} p(x) K_i(x) dx = \hat{\kappa}_i, \text{ for } i = 1, 2, \cdots, n$$  \hspace{1cm} (A.9)

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

The convexity assumption on $\psi$ allows us to invoke the theory of duality and in particular, the Strong Duality Theorem.\footnote{See Borwein & Lewis (1991) and Decarreau et al. (1992) for more information.} We define the Primal Problem to be:

$$\min_p D(p \to q)$$

subject to:

$$\int p(x) K_i(x) dx = \hat{\kappa}_i, \text{ for } i = 1, 2, \cdots, n$$

$$\int p(x) dx = 1$$

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The corresponding Lagrangian is given by:

\[ L(p : \lambda, \lambda_0) = \int \left[ q(x) \psi \left( \frac{p(x)}{q(x)} \right) - p(x) \sum_{i=0}^{n} \lambda_i K_i(x) \right] dx + \sum_{i=0}^{n} \lambda_i \tilde{\kappa}_i \]  
(A.10)

where \( \lambda = [\lambda_1, \lambda_2, \cdots, \lambda_n]^T \) and \( \lambda_0 \) denotes the set of positive Lagrange multipliers for \( \Omega \).

Under the Strong Duality Theorem, we have the following equivalence:

\[
\min_{p \in \mathbb{P}} \{ D(p \to q) \} = \max_{\lambda, \lambda_0} \left\{ \inf_{p \in \mathbb{P}} L(p : \lambda, \lambda_0) \right\} \]  
(A.11)

The equivalent Dual Problem is given by:

\[
\max_{\lambda, \lambda_0} \left\{ \inf_{p \in \mathbb{P}} L(p : \lambda, \lambda_0) \right\} 
\text{subject to : } \lambda \geq 0 
\]  
(A.12)

In order to solve the Dual Problem, we define \( F = q(x) \psi \left( \frac{p(x)}{q(x)} \right) - p(x) \sum_{i=0}^{n} \lambda_i K_i(x) \) and set \( \frac{\partial F}{\partial p} = 0 \), this yields:

\[
\psi ' \left( \frac{p(x)}{q(x)} \right) = \sum_{i=0}^{n} \lambda_i K_i(x) 
\]  
(A.13)

Under the convexity assumption, the function \( \psi '(x) \) has a unique inverse over the positive reals. Thus we can explicitly solve for \( p(x) \):

\[
p(x) = q(x) \psi '^{-1} \left( \sum_{i=0}^{n} \lambda_i K_i(x) \right) 
\]  
(A.14)

Substituting Eqn. A.14 into Eqn. A.10 yields:

\[
L^*(\lambda, \lambda_0) = \inf_{p \in \mathbb{P}} L(p : \lambda, \lambda_0) 
\]

\[
= \mathbb{E}_q \left[ \psi \left( \psi '^{-1} \left( \sum_{i=0}^{n} \lambda_i K_i(X) \right) \right) \right] - \sum_{j=0}^{n} \left\{ \lambda_j \mathbb{E}_q \left[ K_j(X) \psi '^{-1} \left( \sum_{i=0}^{n} \lambda_i K_i(X) \right) \right] \right\} + \sum_{i=0}^{n} \lambda_i \tilde{\kappa}_i
\]
Defining $\Psi'(x) = \psi^{-1}(x) \iff x = \psi'\left[\Psi'(x)\right]$ and applying integration by parts yields:

$$\Psi(x) = x\Psi'(x) - \psi(\Psi'(x))$$ (A.15)

Using Eqn. A.15 to simplify $L^*(\lambda, \lambda_0)$ yields:

$$L^*(\lambda, \lambda_0) = \sum_{i=0}^{n} \lambda_i \hat{k}_i - \mathbb{E}_q \left[ \Psi\left(\sum_{i=0}^{n} \lambda_i K_i(x)\right)\right]$$ (A.16)

Substituting Eqn. A.16 into Eqn. A.12 and simplifying using $\Psi'(x) = \psi^{-1}(x)$ yields the simplest form of the Dual Problem:

$$\max_{\lambda, \lambda_0} L^*(\lambda, \lambda_0) = \sum_{i=0}^{n} \lambda_i \hat{k}_i - \mathbb{E}_q \left[ \Psi\left(\sum_{i=0}^{n} \lambda_i K_i(x)\right)\right]$$ (A.17)

The Gradient of $L^*$ with respect to $\lambda_j$ is defined as:

$$\frac{\partial L^*}{\partial \lambda_j} = -\mathbb{E}_q \left[ K_j(x)\Psi'\left(\sum_{i=0}^{n} \lambda_i K_i(x)\right)\right] + \hat{k}_j \text{ for } j = 0, 1, \ldots, n$$ (A.18)

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

$$\mathbb{E}_q \left[ \Psi'\left(\sum_{i=0}^{n} \lambda_i K_i(x)\right)\right] = 1$$ (A.19)

$$\mathbb{E}_q \left[ K_1(x)\Psi'\left(\sum_{i=0}^{n} \lambda_i K_i(x)\right)\right] = \hat{k}_1$$ (A.20)

$$\vdots$$

$$\mathbb{E}_q \left[ K_n(x)\Psi'\left(\sum_{i=0}^{n} \lambda_i K_i(x)\right)\right] = \hat{k}_n$$ (A.21)

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

$$\frac{1}{n} \sum_{k=1}^{n} K_j(x_k)\Psi'\left(\sum_{i=0}^{n} \lambda_i K_i(x_k)\right) = \hat{k}_j \text{ where } \{X_k\}_{k=1}^{n} \sim q \text{ and } j = 0, 1, \ldots, n$$ (A.22)
The solution to this set of equations provides a set of consistent estimators for the Lagrange multipliers \( \hat{\lambda} = [\hat{\lambda}_1, \hat{\lambda}_2, \ldots, \hat{\lambda}_n]^T \) and \( \hat{\lambda}_0 \).

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

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

The K-L measure is strictly convex as \( \Psi''(x) = \frac{1}{x} > 0 \) \( \forall x \in \mathbb{R}^+ \). Under this measure, the Csiszar Cross Entropy distance is defined as:

\[
D(p \rightarrow q) = \int_\zeta q(x) \ln \left( \frac{p(x)}{q(x)} \right) dx
\]

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

Our constraint set \( \Omega \) is the set \( \mathbb{E}_p [K_i(X)] = \hat{\kappa}_i \) for \( i = 0, 1, \ldots, n \) where \( \hat{\kappa}_0 = 1 \) and \( K_0(\cdot) = 1 \).

We define \( \{K_i(x)\}_{i=0}^n = \{\chi_i(x)\}_{i=0}^n \) where \( \chi_i(x) \) 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:

\[
\mathbb{E}_p [\chi_i(X)] = \hat{\kappa}_i \text{ for } i = 0, 1, \ldots, n \tag{A.23}
\]

The Primal Problem is defined as:

\[
\min_p D(p \rightarrow q) = \int_\zeta q(x) \ln \left( \frac{p(x)}{q(x)} \right) dx
\]

subject to \( \mathbb{E}_p [\chi_i(X)] = \hat{\kappa}_i \) for \( i = 0, 1, \ldots, n \)

The solution to the Primal Problem using Eqn. A.14 is given by:

\[
p(x) = q(x) \exp \left[ \sum_{i=0}^n \lambda_i \chi_i(x) - 1 \right] \tag{A.24}
\]

To see the equivalence between Eqn. A.24 and the CIMDO posterior distribution given by Eqn. A.7, define the Lagrange multipliers to be inherently negative and denote \( \lambda_0 \) as \( \mu \), this
yields the following equivalent expression:

\[
\hat{p}(x) = q(x) \exp \left\{ - \left[ 1 + \hat{\mu} + \sum_{i=1}^{n} \hat{\lambda}_i \chi_i(x) \right] \right\}
\]  
(A.25)

We use Eqn. A.17 to solve for the Lagrange multipliers:

\[
\max_{\lambda, \lambda_0} \left\{ \sum_{i=0}^{n} \lambda_i \text{PoD}_i - \mathbb{E}_q \left[ \exp \left( \sum_{i=0}^{n} \lambda_i \chi_i(X) - 1 \right) \right] \right\}
\]  
(A.26)

where \( \text{PoD}_0 = 1 \) and \( \chi_0(\cdot) = 1 \).

To maximize Eqn. A.26, we solve the following system of equations:

\[
\mathbb{E}_q \left[ \exp \left( \sum_{i=0}^{n} \lambda_i \chi_i(X) - 1 \right) \right] = 1 \quad (A.27)
\]

\[
\mathbb{E}_q \left[ \chi_1(X) \exp \left( \sum_{i=0}^{n} \lambda_i \chi_i(X) - 1 \right) \right] = \text{PoD}_1 \quad (A.28)
\]

\[ \vdots \]

\[
\mathbb{E}_q \left[ \chi_n(X) \exp \left( \sum_{i=0}^{n} \lambda_i \chi_i(X) - 1 \right) \right] = \text{PoD}_n \quad (A.29)
\]

We numerically solve the above system of equations using Eqn. A.22 thereby obtaining a set of consistent estimators for the Lagrange multipliers \( \hat{\mu}, \hat{\lambda}_1, \ldots, \hat{\lambda}_n \).
A.4. Estimating the Distance to Default (DTD)

An institution’s equity can be viewed as a call option on its underlying assets since at the maturity of the institution’s liabilities, bondholders receive their debt and equity holders obtain the rest. Denote the observable value and volatility of equity as $V_E$ and $\sigma_E$, respectively and denote the unobservable value and volatility of the institution’s assets as $V_A$ and $\sigma_A$, respectively. Under the Merton (1974) model, the asset value follows a geometric Brownian motion:

$$dV_A = \mu_A V_A dt + \sigma_A V_A dW$$

where $\mu_A$ denotes the drift term and $dW$ is a Wiener process.

Under the Black-Scholes option pricing theory, we price the value of equity as a call option:

$$V_E(t) = V_A(t) \Phi(d_1) - \exp(-r(T-t))D\Phi(d_2)$$

Using Ito’s formula, we have:

$$\sigma_E = \frac{V_A}{V_E} \frac{\partial V_E}{\partial V_A} \sigma_A$$

where $d_1 = \left[ \log(V_A(t)/D) + (r + \sigma_A^2/2) (T-t) \right] / (\sigma_A \sqrt{T-t})$, $d_2 = d_1 - \sigma_A \sqrt{T-t}$, $D$ is the book value of total liabilities, $T$ is the liabilities’ maturity and $r$ is the risk-free rate.

The unique set of solutions for $V_A$ and $\sigma_A$ is obtained by solving the following system of equations:

$$V_A(t) \Phi(d_1) - \exp(-r(T-t))D\Phi(d_2) - V_E(t) = 0 \quad (A.30)$$

$$\frac{V_A}{V_E} \Phi(d_1) \sigma_A - \sigma_E = 0 \quad (A.31)$$

We define the DTD to be:

$$DTD(t) = \frac{\log \left( \frac{V_A}{D} \right) + \left( r - \frac{\sigma_A^2}{2} \right) (T-t)}{\sigma_A \sqrt{T-t}}$$

For our purposes, we use the 1-year DTD, thus we set $T-t = 1$. 56
B. Figures

Figure 1: Summary of probability of default (PoD) and distance to default (DTD)
Panel A presents the average five-year annualized bootstrapped probabilities of default for the 10 euro area (EA) sovereigns listed in Table 1 and the 26 EA banks listed in Table 2. USD-denominated (euro-denominated) CDS spreads of maturities one to five years are used to derive the sovereign (bank) probabilities of default. Panel B presents the average distance to default of the banking system. The distance to default measures how far an institution is away from default in units of standard deviation, it is used to proxy for the physical probabilities of default. The sample period for both panels is from 1 January 2008 to 28 February 2013.

Panel A: Summary of sovereign and bank PoD

Panel B: Summary of bank DTD
Figure 2: **Bank correlations based on equity returns**

Panel A presents the mean, maximum (Max) and minimum (Min) pairwise correlations over the full sample of the 26 euro area banks listed in Table 2. Pairwise correlation is defined as the average correlation coefficient of each bank with all other banks. Correlation coefficients are calculated based on a rolling window of the past one year of daily arithmetic equity returns of each bank with all other banks. Panel B presents the average pairwise bank correlations sorted by originating sovereign. Each series represents the average pairwise correlation of banks within the corresponding sovereign listed in the legend with all other banks in the banking system. The abbreviations of the sovereigns are listed in Table 1. The sample period for both panels is from 1 January 2008 to 28 February 2013.
Figure 3: **Sovereign probability of default (PoD) and joint probability of default (JPoD)**

Panel A presents the five-year annualized bootstrapped probabilities of default for each of the 10 euro area (EA) sovereigns listed in Table 1. USD-denominated CDS spreads of maturities one to five years are used to derive the sovereign probabilities of default. Panel B presents the joint probability of default for the 10 EA sovereigns listed in Table 1. Each series represents the joint probability of default of the corresponding sovereign listed in the legend with all the other sovereigns. The correlation matrix used to derive the sovereign joint probability of default is given in Table 3. The sample period for both panels is from 1 January 2008 to 28 February 2013.
Figure 4: **Sovereign conditional joint probability of default (CoJPoD) and change in the conditional joint probability of default (∆CoJPoD)**

Panel A presents the conditional joint probabilities of default for the 10 euro area (EA) sovereigns listed in Table 1. Each series represents the conditional joint probability of default of the rest of the sovereign system, given the default of the corresponding sovereign listed in the legend. Panel B presents the change in the conditional joint probabilities of default for the 10 EA sovereigns listed in Table 1. Each series represents the change in the conditional joint probability of default of the rest of the sovereign system, given the default of the corresponding sovereign listed in the legend. ∆CoJPoD is derived by computing the difference between the CoJPoD and the JPoD of each series. The correlation matrix used to derive the sovereign CoJPoD and ∆CoJPoD is given in Table 3. The sample period for both panels is from 1 January 2008 to 28 February 2013.
Panel A presents the five-year annualized bootstrapped probabilities of default for the 26 euro area (EA) banks listed in Table 2. Each series represents the average probability of default of the banks within the corresponding sovereign listed in the legend. Euro-denominated CDS spreads of maturities one to five years are used to derive the bank probabilities of default. Panel B presents the joint probability of default of the banking system with each of the 10 EA sovereigns listed in Table 1. Each series represents the joint probability of default of the banking system and the corresponding sovereign listed in the legend. Non-zero correlation matrices based on daily changes in the five-year CDS spreads of sovereign and bank CDS contracts are used to derive bank JPoD. The sample period for both panels is from 1 January 2008 to 28 February 2013.
Figure 6: Bank conditional joint probability of default (CoJPoD) and change in the conditional joint probability of default (ΔCoJPoD)

Panel A presents the conditional joint probability of default of the banking system. Each series represents the conditional joint probability of default of the banking system, given the default of the corresponding sovereign listed in the legend. Panel B presents the change in the conditional joint probability of default of the banking system. Each series represents the change in the conditional joint probability of default of the banking system, given the default of the corresponding sovereign listed in the legend. ΔCoJPoD is derived by computing the difference between the CoJPoD and the JPoD of each series. The abbreviations of the sovereigns are listed in Table 1 and the originating sovereign of each bank is listed in Table 2. Non-zero correlation matrices based on daily changes in the five-year CDS spreads of sovereign and bank CDS contracts are used to derive bank CoJPoD and ΔCoJPoD. The sample period for both panels is from 1 January 2008 to 28 February 2013.
Panel A presents the full sample average conditional joint probability of default of the 26 euro area (EA) banks. The series is formed by averaging the conditional joint probability of default of the banking system, given the default of each of the 10 EA sovereigns (shown in Fig. 6, Panel A). Non-zero correlation matrices based on daily changes in the five-year CDS spreads of sovereign and bank CDS contracts are used to derive bank CoJPoD. The list of 10 EA sovereigns and 26 EA banks are provided in Table 1 and Table 2, respectively. The sample period for Panel A is from 1 January 2008 to 28 February 2013. Panel B presents the distressed insurance premium of the banking system. The series represents the unit price (in %) for insuring against financial distress. Financial distress is defined as the situation when at least 10% of total liabilities in the banking system defaults. The sample period for panel B is from 2002 to 2013.
Figure 8: **Bank CoJPoD - financial crisis**

This figure presents the average conditional joint probability of default of the 26 euro area banks during the global financial crisis. This figure is a truncated version of Fig. 7, with the sample period restricted from 1 January 2008 to 31 December 2009. Major events are denoted by dashed vertical lines.

(2) 7 July 2008: Freddie Mac, Fannie Mae plunge on capital concerns.
(3) 15 September 2008: Lehman Brothers files biggest bankruptcy after suitors balk.
(4) 15 November 2008: G20 Summit seeks to boost growth and prevent crises.
(5) 10 March 2009: Stock market hits bottom as measured by the Dow Jones Industrial Average.
(6) 2 April 2009: G20 to set up Financial Stability Board.
Figure 9: Bank CoJPoD - sovereign debt crisis
This figure presents the average conditional joint probability of default of the 26 euro area banks during the sovereign debt crisis. This figure is a truncated version of Fig. 7, with the sample period restricted from 1 January 2010 to 28 February 2013. Major events are denoted by dashed vertical lines.

(1) 2 May 2010: The EA countries and the IMF agree on a €110 billion loan package to Greece.
(2) 23 July 2010: The Committee of European Banking Supervisors publishes the results of the banking stress tests.
(3) 7 December 2010: EU-IMF package for Ireland agreed.
(4) 12 January 2011: News regarding the expansion of the European Financial Stability Facility dissipated into the financial markets.
(5) 19 February 2011: G20 to focus on imbalances.
(6) 15 July 2011: The European Banking Authority publishes the results of the 2011 round of banking stress tests.
(7) 14 October 2011: G20 pledges to preserve financial stability.
(8) 30 November 2011: The Federal Reserve coordinates global effort with other central banks to lower prices on dollar liquidity swaps.
(9) 21 December 2011: The ECB implemented the first 3-year long-term refinancing operation, offering loans at low interest rates.
(10) 21 February 2012: Eurogroup agrees on second financial aid package for Greece.
(11) 27 June 2012: Both Spain and Cyprus seek financial support from EA members.
(12) 20 July 2012: Eurogroup grants financial assistance to Spain’s banking sector.
C. Tables

Table 1: **List of sovereign abbreviations**
This table presents the 10 euro area sovereigns used in our paper. The first column shows the abbreviations of the sovereigns. The second column shows the full name of the sovereigns.

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Table 2: **List of bank abbreviations**
This table presents the 26 euro area banks used in our paper. The first column shows the originating sovereign of the banks. The second column shows the abbreviations of the banks. The third column shows the full name of the banks.

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<th>Bank Abbreviation</th>
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Table 3: **Sovereign correlation matrix**

This table presents the correlation matrix between the 10 euro area 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 USD-denominated and the sample period is from 1 January 2008 to 28 February 2013.

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<td>0.50</td>
<td>0.69</td>
<td>0.64</td>
<td>0.49</td>
<td>0.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GER</td>
<td>1.00</td>
<td>0.12</td>
<td>0.46</td>
<td>0.59</td>
<td>0.66</td>
<td>0.45</td>
<td>0.59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GRE</td>
<td>1.00</td>
<td>0.11</td>
<td>0.13</td>
<td>0.11</td>
<td>0.12</td>
<td>0.15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IRE</td>
<td>1.00</td>
<td>0.55</td>
<td>0.43</td>
<td>0.65</td>
<td>0.59</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ITA</td>
<td>1.00</td>
<td>0.56</td>
<td>0.80</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NL</td>
<td>1.00</td>
<td>0.33</td>
<td>0.52</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POR</td>
<td>1.00</td>
<td>0.60</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPA</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4: **Description of variables and data sources**

This table presents the variable names, descriptions and data sources of all the variables that we use in this paper.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  CDS spreads</td>
<td>We use daily CDS mid rate spreads with maturities of one to five years. USD-denominated (EUR-denominated) CDS contracts are used for sovereigns (banks). All CDS contracts are of the form ‘Modified-Modified’ (MM).</td>
<td>Datastream</td>
</tr>
<tr>
<td>2  EUR/USD FX rate</td>
<td>Historical daily euro-dollar exchange rate.</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>3  EA bond yields</td>
<td>Daily AAA EA government bond yields of maturities three months to five years.</td>
<td>Datastream</td>
</tr>
<tr>
<td>4  Balance sheet items</td>
<td>Annual data is used for the total book value of assets and liabilities. Daily data is used for stock prices and market value of equity.</td>
<td>Datastream</td>
</tr>
<tr>
<td>5  Risk-free rate</td>
<td>We use the daily five-year implied swap rate.</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>6  Default risk premium</td>
<td>Daily difference between the yields of ten-year euro zone industrials rated BBB and those rated AA+/AA.</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>7  Liquidity risk premium</td>
<td>Daily three-month euro LIBOR/OIS (or EURIBOR/EONIA) spread.</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>8  Sovereign risk premium</td>
<td>Daily difference between Germany’s ten-year generic yield with the average of the Spanish and Italian ten-year generic yields weighted by their quarterly real GDPs.</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>9  Stock market returns</td>
<td>Daily stock market returns of the main stock market indices of each sovereign.</td>
<td>Datastream</td>
</tr>
<tr>
<td>10 GDP</td>
<td>Quarterly real GDP using year 2000 euro prices.</td>
<td>Datastream</td>
</tr>
<tr>
<td>11 Debt/GDP</td>
<td>Government debt-to-GDP ratio.</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>12 Reserve/Debt</td>
<td>Total reserves (without gold)-to-government debt ratio.</td>
<td>Bloomberg</td>
</tr>
<tr>
<td>13 Term spread</td>
<td>Difference between the ten-year and three-month AAA euro area bond yields.</td>
<td>Datastream</td>
</tr>
<tr>
<td>14 VSTOXX</td>
<td>24-month VSTOXX volatility index.</td>
<td>Datastream</td>
</tr>
</tbody>
</table>
Table 5: Summary of key default risk variables
This table presents the mean values of seven key default risk variables for the 10 euro area (EA) sovereigns listed in Table 1 and 26 EA banks listed in Table 2. Period 1, denoted (1), is from 1 January 2008 to 31 December 2009. Period 2, denoted (2), is from 1 January 2010 to 28 February 2013. Sov CDS is the average five-year sovereign CDS mid rate spreads. Bank CDS is the average five-year bank CDS mid rate spreads of all the banks within the same sovereign. Sov PoD is the average annualized sovereign probability of default. Bank PoD is the average annualized bank probability of default of all the banks within the same sovereign. Bank DTD is the average bank distance to default of all the banks within the same sovereign. Total Assets is the average total book value of assets of all the banks within the same sovereign. Total Liabilities is the average total book value of liabilities of all the banks within the same sovereign. Sov CDS and Bank CDS are measured in basis points. Bank DTD is measured in units of standard deviations. Sov PoD and Bank PoD are measured in %. Total Assets and Total Liabilities are measured in millions of euros.

<table>
<thead>
<tr>
<th>Sovereigns</th>
<th>Sov CDS (1)</th>
<th>Bank CDS (1)</th>
<th>Sov PoD (1)</th>
<th>Bank PoD (1)</th>
<th>Bank DTD (1)</th>
<th>Total Assets (1)</th>
<th>Total Liabilities (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>69.86</td>
<td>101.31</td>
<td>188.37</td>
<td>194.23</td>
<td>1.18</td>
<td>3.12</td>
<td>5.07</td>
</tr>
<tr>
<td>BEL</td>
<td>49.04</td>
<td>164.68</td>
<td>199.11</td>
<td>358.83</td>
<td>0.84</td>
<td>2.78</td>
<td>3.28</td>
</tr>
<tr>
<td>GER</td>
<td>25.69</td>
<td>57.11</td>
<td>94.24</td>
<td>156.62</td>
<td>0.44</td>
<td>0.98</td>
<td>1.59</td>
</tr>
<tr>
<td>SPA</td>
<td>67.07</td>
<td>246.54</td>
<td>133.52</td>
<td>338.62</td>
<td>1.14</td>
<td>4.10</td>
<td>2.23</td>
</tr>
<tr>
<td>FRA</td>
<td>30.18</td>
<td>113.95</td>
<td>110.61</td>
<td>184.15</td>
<td>0.52</td>
<td>1.94</td>
<td>1.85</td>
</tr>
<tr>
<td>IRE</td>
<td>127.65</td>
<td>486.67</td>
<td>242.86</td>
<td>845.14</td>
<td>2.13</td>
<td>7.63</td>
<td>4.00</td>
</tr>
<tr>
<td>ITA</td>
<td>83.83</td>
<td>285.42</td>
<td>97.66</td>
<td>335.01</td>
<td>1.42</td>
<td>4.74</td>
<td>1.64</td>
</tr>
<tr>
<td>NL</td>
<td>38.49</td>
<td>64.83</td>
<td>146.72</td>
<td>174.20</td>
<td>0.65</td>
<td>1.11</td>
<td>2.42</td>
</tr>
<tr>
<td>POR</td>
<td>64.09</td>
<td>659.35</td>
<td>106.95</td>
<td>716.12</td>
<td>1.09</td>
<td>9.93</td>
<td>1.80</td>
</tr>
</tbody>
</table>
Table 6: Determinants of full sample bank and sovereign conditional joint probability of default (CoJPoD)

This table presents the determinants of the full sample bank and sovereign conditional joint probability of default. Panel A (Panel B) reports the determinants of bank CoJPoD (sovereign CoJPoD). Bank CoJPoD is the full sample average conditional joint probability of default of the banking system, given the default of each of the 10 euro area (EA) sovereigns. Sovereign CoJPoD is the full sample average conditional joint probability of default of the sovereign system, given the default of each of the 10 EA sovereigns. Bank PoD is the bank probability of default averaged over the 26 EA banks listed in Table 2. Bank Corr is the average pairwise correlation coefficient of each bank with all other banks. Correlation coefficients are calculated based on a rolling window of the past one year of daily arithmetic equity returns of each bank. Bank PoD Stdev is the standard deviation of the probabilities of default of the 26 EA banks calculated at each point in time. Bank Corr Stdev is the standard deviation of the average pairwise correlation coefficient of the 26 EA banks calculated at each point in time. Sovereign PoD is the sovereign probability of default averaged over the 10 EA sovereigns listed in Table 1. Sovereign Corr is the average pairwise correlation coefficient of each sovereign with all other sovereigns. Correlation coefficients are calculated based on a rolling window of the past one year of daily arithmetic stock market returns of each sovereign. We use the main stock market index of each sovereign to compute daily stock market returns. Sovereign PoD Stdev is the standard deviation of the probabilities of default of the 10 EA sovereigns calculated at each point in time. Sovereign Corr Stdev is the standard deviation of the average pairwise correlation coefficient of the 10 EA sovereigns calculated at each point in time. The sample consists of daily observations from 1 January 2008 to 28 February 2013. Ordinary least squares regression is adopted for both panels. t-statistics are shown in parentheses and are based on heteroskedasticity and autocorrelation consistent Newey-West standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
Panel A: Determinants of bank CoJPoD

<table>
<thead>
<tr>
<th>Indep. variables</th>
<th>Dependent variables</th>
<th>Bank CoJPoD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.048***</td>
<td>0.401***</td>
</tr>
<tr>
<td></td>
<td>(40.341)</td>
<td>(10.320)</td>
</tr>
<tr>
<td>Bank PoD</td>
<td>2.591***</td>
<td>2.579***</td>
</tr>
<tr>
<td></td>
<td>(94.593)</td>
<td>(89.580)</td>
</tr>
<tr>
<td>Bank Corr</td>
<td>−0.503***</td>
<td>−0.013</td>
</tr>
<tr>
<td></td>
<td>(−6.694)</td>
<td>(−0.991)</td>
</tr>
<tr>
<td>Bank PoD Stdev</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank Corr Stdev</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of obs.</td>
<td>1348</td>
<td>1348</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.982</td>
<td>0.164</td>
</tr>
</tbody>
</table>

Panel B: Determinants of sovereign CoJPoD

<table>
<thead>
<tr>
<th>Indep. variables</th>
<th>Dependent variables</th>
<th>Sovereign CoJPoD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.106***</td>
<td>0.153***</td>
</tr>
<tr>
<td></td>
<td>(22.103)</td>
<td>(4.074)</td>
</tr>
<tr>
<td>Sovereign PoD</td>
<td>2.374***</td>
<td>2.364***</td>
</tr>
<tr>
<td></td>
<td>(33.285)</td>
<td>(36.138)</td>
</tr>
<tr>
<td>Sovereign Corr</td>
<td>0.078*</td>
<td>0.055***</td>
</tr>
<tr>
<td></td>
<td>(1.677)</td>
<td>(3.239)</td>
</tr>
<tr>
<td>Sovereign PoD Stdev</td>
<td></td>
<td>−1.127***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(−15.842)</td>
</tr>
<tr>
<td>Sovereign Corr Stdev</td>
<td></td>
<td>0.081</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.331)</td>
</tr>
<tr>
<td>No. of obs.</td>
<td>1348</td>
<td>1348</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.850</td>
<td>0.016</td>
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</tbody>
</table>
Table 7: Decomposition of full sample bank and sovereign conditional joint probability of default (CoJPoD)

This table presents the decomposition of the full sample bank and sovereign conditional joint probability of default. Panel A (Panel B) reports the decomposition of bank CoJPoD (sovereign CoJPoD). Bank CoJPoD is the full sample average conditional joint probability of default of the banking system, given the default of each of the 10 euro area (EA) sovereigns. Sovereign CoJPoD is the full sample average conditional joint probability of default of the sovereign system, given the default of each of the 10 EA sovereigns. DTD is the average distance to default of the 26 EA banks. DRP is the default risk premium calculated by using the daily difference between the yields of ten-year euro zone industrials rated BBB and those rated AA+/AA. LRP is the liquidity risk premium calculated by using the daily three-month euro LIBOR/OIS (or EURIBOR/EONIA) spread. SRP is the sovereign risk premium calculated by using the daily difference between Germany’s ten-year generic yield with the average of the Spanish and Italian ten-year generic yields weighted by their quarterly real GDPs. All dependent variables and independent variables, except for DTD, are measured in %. The sample consists of monthly observations from 1 January 2008 to 31 December 2012. Ordinary least squares regression is adopted for both panels. *-statistics are shown in parentheses and are based on heteroskedasticity and autocorrelation consistent Newey-West standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
Panel A: Decomposition of bank CoJPoD

<table>
<thead>
<tr>
<th>Indep. variables</th>
<th>Dependent variables</th>
<th>Bank CoJPoD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Constant</td>
<td>17.600***</td>
<td>18.014***</td>
</tr>
<tr>
<td></td>
<td>(10.980)</td>
<td>(8.990)</td>
</tr>
<tr>
<td>DTD</td>
<td>-12.581***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.661)</td>
<td></td>
</tr>
<tr>
<td>DRP</td>
<td>-1.730***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.906)</td>
<td></td>
</tr>
<tr>
<td>LRP</td>
<td>8.410***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(14.143)</td>
<td></td>
</tr>
<tr>
<td>SRP</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of obs.</td>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.363</td>
<td>0.048</td>
</tr>
</tbody>
</table>

Panel B: Determinants of sovereign CoJPoD

<table>
<thead>
<tr>
<th>Indep. variables</th>
<th>Dependent variables</th>
<th>Sovereign CoJPoD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>(10.545)</td>
<td>(8.670)</td>
</tr>
<tr>
<td>DTD</td>
<td>-20.171***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.795)</td>
<td></td>
</tr>
<tr>
<td>DRP</td>
<td>-3.190***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.669)</td>
<td></td>
</tr>
<tr>
<td>LRP</td>
<td>-4.596</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.130)</td>
<td></td>
</tr>
<tr>
<td>SRP</td>
<td>12.648***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.569)</td>
<td></td>
</tr>
<tr>
<td>No. of obs.</td>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.362</td>
<td>0.069</td>
</tr>
</tbody>
</table>
This table presents a set of panel ordinary least squares regressions to examine the predictive power of economic fundamentals, using monthly observations from the period 1 January 2008 to 28 February 2013. CoJPoD is the dependent variable in columns (1) to (2). CoJPoD is the dependent variable in columns (3) to (4). CoJPoD is the dependent variable in columns (5) to (6). CoJPoD is the conditional joint probability of default of the sovereign system, given the default of a particular sovereign. CoJPoD is the conditional joint probability of default of a particular sovereign, given the default of the sovereign system. CoJPoD is the conditional joint probability of default of the banking system, given the default of a particular sovereign. CoJPoD is the conditional joint probability of default of a particular sovereign, given the default of the banking system. Market Ret (6 mo. rolling) is the six-month rolling arithmetic returns of the main stock market index of each sovereign. Market Vol (6 mo. rolling) is the six-month rolling standard deviations of the daily arithmetic returns of the main stock market index of each sovereign. Market Ret (1 mo. avg) is the monthly average arithmetic returns of the main stock market index of each sovereign. Market Vol (1 mo. avg) is the monthly average standard deviations of the daily arithmetic returns of the main stock market index of each sovereign. Log GDP is the natural logarithm of the real GDP based on year 2000 euro prices. Debt/GDP is the total government debt-to-GDP ratio. Reserve/Debt is the total reserves (excluding gold)-to-government debt ratio. Term Spread is the difference between the ten-year and three-month AAA euro area bond yields. VSTOXX is the 24-month VSTOXX volatility index. All independent variables except for Log GDP are measured in %. All independent variables except for Term Spread and VSTOXX are lagged by 1 year. t-statistics are shown in parentheses and are based on White heteroskedasticity-consistent standard errors clustered by sovereign. Sovereign fixed effects are included in all regressions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Conditional joint probability of default (CoJPoD) and economic fundamentals
| Indep. variables | CoJPoD\(_{\text{sov system|sov}}\) | CoJPoD\(_{\text{sov|sov system}}\) | CoJPoD\(_{\text{bank system|sov}}\) | CoJPoD\(_{\text{sov|bank system}}\) |
|------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| Market Ret       | \(0.001^{***}\) \(-3.600\) \(0.000\) \(-2.607\) \(-2.931\) | \(4.759\) \(3.880\) \(0.000^{*}\) | \(-0.000^{*}\) | \(-1.862^{*}\) |
| Market Vol       | 0.008 \(0.464\) \(-0.008\) \(-0.008\) \(-0.008\) | \(-0.008\) \(-0.008\) | \(-0.001\) | \(-0.001\) |
| Log GDP          | 0.913*** \(2.922\) \(3.235\) \(-3.180\) \(-3.138\) | \(-1.180^{***}\) \(-1.239^{***}\) \(-2.237^{***}\) \(-2.237^{***}\) \(-1.492^{**}\) \(-1.505^{**}\) | \(-0.020^{**}\) \(-2.118^{*}\) \(-2.283^{**}\) \(-2.490^{**}\) \(-3.976^{**}\) |
| Debt/GDP         | \(0.004^{***}\) \(0.004^{***}\) \(0.004^{***}\) \(0.004^{***}\) \(0.003^{***}\) | \(-0.004^{*}\) \(-0.004^{*}\) \(-0.004^{*}\) \(-0.004^{*}\) \(-0.003^{*}\) | 0.003 | 0.003 |
| Reserve/Debt     | \(0.069^{**}\) \(0.071^{**}\) \(0.075^{**}\) \(0.073^{**}\) \(0.051^{**}\) | \(-0.008^{***}\) \(-0.008^{***}\) \(-0.008^{***}\) \(-0.008^{***}\) \(-0.008^{***}\) | 0.053 | 0.055 |
| Term Spread      | \(0.042^{**}\) \(0.042^{**}\) \(0.012\) \(0.015^{**}\) \(0.012^{**}\) | \(-0.012^{**}\) \(-0.012^{**}\) \(-0.012^{**}\) \(-0.012^{**}\) \(-0.003^{*}\) \(-0.002^{*}\) | 0.005 | 0.007 |
| VSTOXX           | \(0.004^{***}\) \(0.004^{***}\) \(0.008^{***}\) \(0.008^{***}\) \(0.003^{***}\) | \(-0.008^{***}\) \(-0.008^{***}\) \(-0.008^{***}\) \(-0.008^{***}\) \(-0.008^{***}\) | \(-0.008^{***}\) \(-0.008^{***}\) \(-0.008^{***}\) | \(-0.008^{***}\) \(-0.008^{***}\) |
| Sovereign fixed eff. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of obs.      | 620 | 620 | 620 | 620 | 620 | 620 | 620 | 620 |
| Adjusted \(R^2\) | 0.728 | 0.720 | 0.822 | 0.822 | 0.718 | 0.721 | 0.784 | 0.785 |