Measuring systemic risk and contagion in the European financial network

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Abstract
This paper introduces a novel framework to study default dependence and systemic risk in a financial network that evolves over time. We analyse several indicators of risk, and develop a new latent space model to assess the health of key European banks before, during and after the recent financial crises. We propose a new statistical model that permits a latent space visualisation of the financial system. This provides a clear and interpretable model-based summary of the interaction data, and it gives a new perspective on the topology structure of the network. Crucially, the methodology provides a new approach to assess and understand the systemic risk associated with a financial system, and to study how debt may spread between institutions. Our dynamic framework provides an interpretable map that illustrates the default dependencies between institutions, highlighting the possible patterns of contagion and the institutions that may pose systemic threats.

Keywords Finance · Default probability · Financial contagion · Latent space models · Financial networks
1 Introduction

Over the last two decades, the global financial system has endured several major crises, most notably the global financial crisis of 2008 and the European Sovereign Debt Crisis in 2010. These events raised serious concerns regarding the resilience of the financial system against the contagion of debt during periods of economic turmoil. The collapse of Lehman Brothers on 15 September 2008 was the largest bankruptcy filing in US history. This financial shock escalated into a global crisis which clearly demonstrated the frailty of the financial ecosystem, and the ineffectiveness of the current regulations. Subsequently, many repercussions were felt throughout the world by the participants of the global financial market, resulting in an excess of cross-border and cross-entity interdependencies (see De Haas and Van Horen 2012; Acharya et al. 2014). By the end of September 2008, the shock had rapidly spread across Europe, where the Euro area governments rescued the Belgian-French bank Dexia. Many authors agree on the fact that the increased interdependencies between the institutions have been playing a crucial role in the spread of contagion, and in forcing hasty responses to the shocks observed in the system (Aiyar 2012; Acemoglu et al. 2015).

Indeed, risk contagion means that foreign shocks will be transmitted to the local market and it reflects a situation where the effect of an external shock is larger than what was expected by experts and analysts (Edwards 2000). This can lead to an increase in the risks of the financial market and of even the whole economic operation, including economic downturn, corporate bankruptcy, liquidity risk, trade surplus slowdown and so on, which raises problems to the local governments (see Cook and Spellman 1996; Beirne and Fratzscher 2013; He et al. 2018; Xu and Gao 2019). In fact, a principle of contagion has been widely applied to explain the phenomenon around the crises of the European Monetary System in 1992–1993, the ‘tequila hangover’ in 1994, the Asian Crises in 1997, and the impact of the Russian crisis on other emerging economies in 1998. Therefore, it is important to investigate the existence of risk contagion, containing causality and measurement of risk contagion (Pais and Stork 2011; Nolde and Zhang 2020). In the financial contagion, the common approach to detect how national economies affect each other (or, differently, to what extent the economic activity is synchronised) is by using cross-correlations between time series (Zheng et al. 2012). Furthermore, there are some works in the literature, including Selover (2004) and Sander and Kleimeier (2003), who propose to apply Granger causality tests; these can be a more sophisticated approach to identify linkages such as cross-country macroeconomic effects and contagion in sovereign debt risk. Granger causality can detect whether one of the time series is useful in forecasting another instead of simply depending on the co-movement between several time series. Because of the existence of time lag in the structure of these models, this method is better suited to identify shock contagion links. More recently, the work by Sebestyén and Iloskics 2020 has focused on the topological properties of the shock contagion network as measured by pairwise Granger causality between economic output of countries. However, as pointed out by Hué et al. (2019) using the pair-wise Granger-causality can lead to spurious causalities that arise because of indirect contagion effects.

More in general, the research on financial networks and systemic risk has developed in many different directions (Bartram et al. 2007; Schweitzer et al. 2009; Engle et al.
2014). A special emphasis has been dedicated to the understanding of how the topology of the system may impact the potential spread of contagion and systemic risk (Elliott et al. 2014; Acemoglu et al. 2015). This research question is of particular importance for both regulators and financial institutions, since these should both be able to clearly identify the primary sources of systemic risk (Acharya et al. 2012), and thus how the risk may be minimised. It is important to provide effective indicators to regulators to prevent or possibly predict systemic contagion. According to Benoit et al. (2017), systemic risk is the likelihood that an entire financial system could be affected by extreme external events, by banks’ large and common exposures, or by an amplification or contagion mechanism that is initiated due to one or several individual extreme losses. Recently, systemic risk in financial systems has been increasingly studied using network theory (Elliott et al. 2014; Delpini et al. 2019). One of the interesting results that has been found is that, when the network is scale-free and the magnitude of negative shocks is large, a more densely connected financial network serves as a mechanism for the propagation of shocks, which results in a more fragile financial system, thus increasing systemic risk Acemoglu et al. (2015).

Giudici et al. (2020) have investigated that correlation network models (with the goal of capturing the multivariate network structure) can provide an efficient means for expressing the indirect dimension of systemic risk through common exposures. Furthermore, they have presented an approach for combining direct exposures and correlations into one measure of systemic risk. Recent theoretical work has shown that interconnectedness can increase systemic risk through various forms of financial contagion, due to common exposures during times of crises (Allen and Babus 2009; Ibragimov et al. 2011; Cai et al. 2018; Wagner 2010). Most studies use a network approach to investigate the interconnectedness between financial institutions. One of the interesting works has been proposed by Billio et al. (2012), who focus on the network topologies of the financial system based on the dependence structure among market prices. By testing Granger causality between banks, insurances and hedge funds, the authors compute several measures of interconnectedness.

Correlation-based networks models that combine financial networks with contagion models emerge from the dependence structure among market prices, and links can be related to Granger causality (Billio et al. 2012; Diebold and Yılmaz 2014) or to pairwise correlations between returns (Tumminello et al. 2010). Some other works have focused on modelling the interactions between multiple channels of contagion. For instance, Poledna et al. (2021) models the interaction between fire sale contagion and contagion due to direct exposures between banks. More recently, Foglia and Angelini (2020) analyses the tail risk spillover between insurance companies, banks and shadow banking systems in the European zone through the tail-event driven network risk model. Their findings suggest the key role of shadow banking in risk transmission (Jin and De Simone 2020; Delpini et al. 2019). A new systemic risk measure, called CoRisk, is studied by Giudici and Parisi (2018). Their measure combines correlation networks with vector autoregression. Moreover, CoRisk can take positive or negative values if the resulting default probability of each country or economic sector can be increased or decreased according to the sign of partial correlations. From an economic point of view, when countries are positively connected to distressed economies, their default probability increases because they suffer negative contagion (Grinis 2015).
particular, the credit default swaps have been used widely in the literature studying risk contagion to understand international and interbank risk propagation (Jiang et al. 2020). As underlined by Eichengreen et al. (2012), the credit default swaps spreads of major banks co-move and reflects market economic prospects.

In practice, we are interested in extracting from the financial system a collection of summaries that can permit an assessment of the risk. In recent years, a number of different measures have been introduced or adapted for this purpose (Giudici and Parisi 2016; Battiston et al. 2012; Friel et al. 2016; Hledik and Rastelli 2018; Agosto et al. 2020). In this paper, we study a dataset of default probabilities for a set of key European banks from 2005 to 2016, and we use a number of measures to assess the risk associated with each of the institutions. First, we use a collection of descriptive statistics and other known indicators that have been introduced in financial networks analyses. Then, we propose a new statistical model that aims at giving a clear and interpretable visualisation of the system by embedding it in a low-dimensional space. An implementation of our estimation algorithm is provided in the form of an R package from our public code repository (Rastelli 2021).

At the foundations of our contribution, we have our constructed measures of dependencies between any given institutions. In general, these may be computed using a number of approaches. One type of approach relies on Pearson’s correlation index (see, e.g., Chi et al. 2010 and Birch et al. 2016). A second approach uses instead the partial correlation index, which measures and filters a network using partial correlation coefficients between banks. The correlation between two financial agents is frequently influenced by other financial agents, that is, two interacting financial agents may also have correlation with other financial agents (see, e.g., Mantegna and Stanley 1999). For instance, the US stock market or the European stock markets can affect on the Hong Kong and Chinese stock markets. Therefore, one can get the pure correlation between the Chinese and Hong Kong stock markets by removing any effects of the US and European stock markets. The partial correlation coefficient quantifies the pure correlation between any two financial agents by measuring the relation between them and deducting the impact of any other financial agents. The approaches that make use of this indicator include (Kenett et al. 2015; Giner et al. 2018; Wen et al. 2019). A third type of approach relies on other correlation-based network methods to construct a network using other similarity measures of correlation (Brida and Risso 2010; Matesanz and Ortega 2014). For instance, Brida and Risso (2010) introduced the tool of symbolic time series analysis to obtain a metric distance between two different stocks; then, the authors used a minimum spanning tree for investigating the correlation structure of the 30 largest North American companies. Furthermore, Matesanz and Ortega (2014) studied the nonlinear co-movements of foreign exchange markets during the Asian currency crisis by combing the minimum spanning tree and phase synchronisation coefficients. The minimum spanning tree is most frequently used since it is a robust, simple and clear tool to visualise the links.

In this paper, we transform the partial correlations to obtain the CoRisk measure (Giudici and Parisi 2016), which quantifies the difference between the unconditional and the conditional probability of default for an institution. This measure effectively captures how much of the risk associated with an institution is due to the risk of its neighbours. We look at the pairwise CoRisk values between the European banks from
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2005 to 2016, hence studying the evolution of this index over time. Then, we propose a different visualisation of the network using minimum spanning trees throughout the same time period, and highlight the importance of nodes using network centrality measures.

Furthermore, we develop a new statistical model that may be used to analyse the nodal attributes of a binary or nonnegatively weighted network. The framework that we consider is inspired by the literature on latent position models (LPMs, Hoff et al. 2002), which has been greatly developed in the last two decades (Handcock et al. 2007; Rastelli et al. 2016; Durante et al. 2017). LPMs postulate that the nodes of a graph are embedded in a latent space (usually $\mathbb{R}^2$), and that a connection between any two nodes becomes more likely if the nodes are close to each other, and less likely if they are far apart. For example, in the context of the recent financial crises, Friel et al. (2016) introduce a type of LPM to study the boards’ compositions for companies quoted on the Irish Stock Exchange. Their approach provides an easy-to-interpret latent space representation of the Irish financial market, and it leads to the introduction of a new potential measure of financial instability. Here, our goal is to offer a new latent space perspective on our data, to ultimately assess the health of European banks during the recent crises.

The rest of this paper is structured as follows. Section 2 describes the proposed methodologies, inference and model interpretation. Section 3 shows the main empirical results for latent position model and analysing the minimum spanning tree networks by using the default probabilities and CoRisk measure. Finally, we provide conclusions with some discussions in Sect. 4.

2 Methodology

2.1 Default probabilities and CoRisk

Our dataset comprises global financial institutions, including banks, tracked by Thomson Reuters every month during the period of 2005 to 2016. For each issuer, we have obtained PDs based on Thomson Reuters’ structural model. Thomson Reuters evaluates the equity market’s view of credit risk via a propitiatory structural default prediction framework based on the Merton model (Merton 1974) which models a company’s equity as a call option on its assets. In this framework, the probability of default (PD) equates to the probability that the option expires worthless. Thomson Reuters produces daily updated estimates of the probability of default or bankruptcy within one year for 35,000 companies globally, including financial firms. The default probabilities are in $1–100$ percentile scores (Pourkhanali et al. 2016).

CoRisk is a measure introduced by Giudici and Parisi (2016) to determine the variation in the probability of default due to contagion effects. The CoRisk measure consists of two components. Firstly, the additional risk taken on by a financial institution due to its connections with other financial institutions is known as $\text{CoRisk}_{in}$. Secondly, the risk caused by the financial institution to other financial institutions that are connected to it is known as $\text{CoRisk}_{out}$. The values for $\text{CoRisk}_{in}$ and $\text{CoRisk}_{out}$ (for bank $j$) can be obtained using the following equations,
\[ CoRisk_{in}^j = 1 - \prod_{i \in ne(j)} (1 - PD^i)^{\rho_{ij|S}}, \] (1)

\[ CoRisk_{out}^j = 1 - \left( 1 - \prod_{i \in ne(j)} (1 - PD^j)^{\rho_{ji|S}} \right), \] (2)

where \( ne(j) \) represents the neighbours of bank \( j \), \( PD^i \) is the probability of default for bank \( i \) and \( \rho_{ij|S} \) is the partial correlation value of banks \( i \) and \( j \) given \( S \) where \( S \) is a set of all other banks.

In order to determine which banks are interconnected in a financial network, a partial correlation matrix is calculated and the partial correlation values are tested for significance. Banks that have a significant partial correlation value with each other are connected by edges in the financial network. We use partial correlation instead of Pearson’s correlation as it provides a more accurate view of the correlation between two banks without the influence of external banks.

Moreover, we are interested in pairwise CoRisk values between any 2 banks to see which connections between banks are the most significant. The CoRisk value between two banks, bank \( i \) and bank \( j \), is defined as follows:

\[ CoRisk_{ij} = 1 - (1 - APD^i)^{\rho_{ij}}, \] (3)

where \( APD^i \) is the average probability of default of bank \( i \) across a specified time period, and \( \rho_{ij} \) is the partial correlation value between bank \( i \) and bank \( j \) over the same time period. Intuitively, this can be interpreted as the effect that the connection of \( i \) and \( j \) has on the probability of default of bank \( j \).

The CoRisk\(_{ij} \) measure has some useful properties. Firstly, CoRisk\(_{ij} < 0 \) if and only if two banks have a negative partial correlation value. It takes a value between 0 and 1, if the two banks have a positive partial correlation value instead. Secondly, the measure is not symmetric, so CoRisk\(_{ij} \neq \) CoRisk\(_{ji} \) unless both banks have the same average default probability. Also, summing up the pairwise CoRisk values from bank \( j \) to other banks and from other banks to bank \( j \) gives us the aggregate measure of CoRisk\(_{out} \) and CoRisk\(_{in} \) values of the bank respectively.

### 2.2 Construction and interpretation of the adjacency matrices

The observed data consist of the values \( Y = \{ y^{(t)}_i \in \mathbb{R} | i = 1, \ldots, N; t = 1, \ldots, T \} \), which denote the log default probabilities, and the edges \( X = \{ x^{(t)}_{ij} \in \{0, 1\} | i, j = 1, \ldots, N; i \neq j \} \), which indicate whether two institutions are highly correlated or not. Here, \( N \) represents the number of financial institutions, and \( t = 1, \ldots, T \) determines the time period considered. The graphs are undirected by construction, that is the edges do not have an orientation and \( x^{(t)}_{ij} = x^{(t)}_{ji} \).

For each \( t = 1, \ldots, T \), the matrix \( X^{(t)} \) can be seen as the binary adjacency matrix representing a random graph. In particular, the value \( x^{(t)}_{ij} \) is equal to one if an edge from node \( i \) to node \( j \) is present at time \( t \), and it is equal to zero otherwise. We obtain
the matrices $X^{(1)}, \ldots, X^{(T)}$ by thresholding at 0.1 the partial correlations introduced in the previous section, that is, we observe an edge between two financial institutions if and only if the corresponding partial correlation is greater than 0.1 in absolute value.

We choose the threshold value 0.1 since this makes the graph densities very close to 0.5 for all time frames. The least connected bank has 11 neighbours, whereas the most connected bank has 23 neighbours, suggesting a fairly regular structure. We aim at an ideal density of 0.5 because this would give us a balanced scenario where we have sufficient information on the neighbourhood of each bank. More importantly, the literature on LPMs suggests that high density graphs are more suitable for latent space modelling, since edges generally provide more information than non-edges when we are interested in inferring latent positions (Raftery et al. 2012; Rastelli et al. 2018).

In order to check the sensitivity to the value 0.1, we also ran all the LPM simulations with threshold value 0.225 (this leads to graph densities close to 0.2) and 0.085 (this leads to graph densities close to 0.65): we did not notice any substantial qualitative change in the results.

2.2.1 Model

LPMs can be considered as generative models for the presence vs absence of edges in a random graph. By contrast, in this paper we are interested in modelling the log default probabilities associated to the nodes of the graph. Our modelling assumption postulates that, at each time, each institution is characterised by a vector of latent coordinates $z_i^{(t)} \in \mathbb{R}_+^2$. These values are model parameters which must be estimated from the observed data. We construct our approach following two core ideas:

1. Institutions located close to each other will tend to exhibit similar default probabilities: the risk on one node will have a certain influence on the risks of the other nearby nodes.

2. The intensity of this contagiousness is determined by the Euclidean distance between the institutions, and by whether the institutions interact with each other or not.

We introduce a new dynamic LPM to model the log default probabilities in the time periods considered. We assume that, conditionally on the latent positions, the likelihood function has the following form:

$$f(y|Z, X) \propto \exp \left\{ -\frac{1}{2} \sum_{t=1}^{T} \sum_{i \neq j} x_{ij}^{(t)} \eta_{ij}^{(t)} \left( y_{i}^{(t)} - y_{j}^{(t)} \right)^2 \right\}.$$  \hspace{1cm} (4)

In the above equation, the summation is over all the pairs of $i, j = 1, \ldots, N$ such that $i \neq j$; $\eta_{ij}^{(t)}$ is a similarity measure and it corresponds to one over the Euclidean distance between the nodes.

The following proposition motivates the likelihood definition in (4).

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1 These are the extreme values observed across all time frames.

2 Results available upon request.
Proposition 1  \textit{The full conditional distribution} $\pi \left( y_i^{(t)} | y_{-(i,t)}, Z, X \right)$ \textit{is a Gaussian distribution with mean} $\mu_i^{(t)}$ \textit{and variance} $\nu_i^{(t)}$ \textit{as follows:}

\[
\mu_i^{(t)} = \frac{\sum_{j=1}^{N} x_{ij}^{(t)} \eta_{ij}^{(t)} y_j^{(t)}}{\sum_{j=1}^{N} x_{ij}^{(t)} \eta_{ij}^{(t)}}, \quad \nu_i^{(t)} = \frac{1}{\sum_{j=1}^{N} x_{ij}^{(t)} \eta_{ij}^{(t)}}. \tag{5}
\]

The symbol $y_{-(i,t)}$ indicates the collection of all observed data with the exception of the $t$-th value of bank $i$. The proof of the proposition is shown in Appendix A. This result underlines a straightforward interpretation for the model: conditionally on all parameters being fixed, the expected log default probability of an institution is equal to the weighted average of the log default probabilities of its graph neighbours, with weights corresponding to the similarity measure given by $\eta_{ij}$. This interpretation is in agreement with the first idea described in Sect. 2.2.1.

In practice, we add a tiny quantity $\varepsilon = 0.001$ to the denominators of 5 to avoid degeneracy whenever a node has no neighbours. With this modification, the full conditional for a node with no neighbours is a Gaussian centred in zero and with a very large variance, which is reasonable since it gives substantial flexibility on the realisation of the corresponding value. If $\varepsilon$ is small enough, the results are not affected.

2.2.2 Hierarchical structure

We create a hierarchical structure and specify prior distributions on the latent positions. This is in close agreement with the literature on LPMs, where Bayesian settings are most commonly used. We consider a standard Gaussian prior on the latent positions, and on the innovations of the latent positions. This means that $z_i^{(1)}$ follows a bivariate Gaussian centred in zero with the identity as covariance matrix; whereas, for $t > 1$, $z_i^{(t)}$ follows a bivariate Gaussian centred in $z_i^{(t-1)}$ with the identity as covariance matrix.

The prior distributions that we use in our set-up may be regarded as informative. As we will discuss in the following sections, our framework relies on an optimisation approach: in this perspective, the prior distributions act as penalisations for the log-likelihood. As a consequence, we do not use these directly to model any prior information that we have on the model parameters, but rather we use them to penalise degenerate scenarios and to emphasise solutions that are most relevant in our context. In practice, we promote small innovations on the latent positions to guarantee that the latent network snapshots remain comparable across times and to facilitate the interpretability of our results.

2.2.3 Inference and model interpretation

The likelihood function which is defined in Eq. 4 specifies the density kernel only up to a proportionality constant. The associated normalising constant does not have an analytical form, and is generally difficult to approximate numerically since it involves the calculation of a $NT$-dimensional integral. Hence, in our approach we deal with a
so-called intractable likelihood (Møller et al. 2006), which creates a connection with a vast literature that deals with similar problems (Friel and Wyse 2012).

When we adopt a Bayesian setting, an intractable likelihood leads to a so-called doubly intractable problem (Murray et al. 2012), whereby a standard implementation of a Markov chain Monte Carlo sampler may not be used efficiently. To circumvent this limitation, we employ a pseudo-likelihood approximation:

\[
 f(y|Z, X) \approx g(y|Z, X) = \prod_{t=1}^{T} \prod_{i=1}^{N} \pi(y_i^{(t)}|y_{-(i,t)}, Z, X).
\] (6)

We assume that the likelihood factorises into the product of the full conditionals of the data points. Thanks to Proposition 1, we know that each of these full conditionals is proportional to a Gaussian, and hence, we are able to compute the pseudo-likelihood exactly and efficiently.

As concerns parameter estimation, we propose to approximate the maximum-a-posteriori estimator using a simulated annealing scheme. Simulated annealing can be seen as a stochastic optimisation algorithm that converges to a maximum of the objective function (Andrieu et al. 2003). In our set-up, the objective function is the pseudo-posterior which can be written as follows:

\[
 \tilde{\pi}(Z|X, y) \propto g(y|Z, X) \pi(Z),
\] (7)

where \(\pi(\cdot)\) denotes a generic prior distribution.

The algorithm tries to update each of the parameters of the model in turn, by obtaining approximate samples from a tempered distribution. When an update of a latent position is attempted, the new value \(z_{new}^{(t)}\) is sampled from a bivariate Gaussian centred in \(z_i^{(t)}\) with identity covariance matrix. Let \(\tilde{\pi}\) be the current value of the objective function, and \(\tilde{\pi}_{new}\) be the new value of the objective after the change. Then, the proposed update is retained with probability \(\min\{1, (\tilde{\pi}_{new}/\tilde{\pi})^{1/\tau_k}\}\), where \(\tau_k\) is the tempering value, which decreases to zero during the procedure.

The optimisation approach allows us to speed up the inferential procedure, and to bypass the likelihood unidentifiability issues that are known to arise with LPMs (Shortreed et al. 2006). However, differently from other computational Bayesian approaches, the optimisation setting does not permit an assessment of the uncertainty around the point estimates that we obtain.

We run our algorithm on the dataset for \(K = 100,000\) iterations, and temperature values defined by \(100e^{-9.21k/K}\), where \(k\) is the iteration index. The algorithm ran in 1.5 h on a 4-cores machine. Figure 1 illustrates the evolution of the calculated objective function during the optimisation.

A large variety of cooling schedules have been employed for simulated annealing algorithms (Winkler 2012). The efficiency of these is highly context dependent, whereby users try out different values of the cooling function until good results are obtained. Generally, the cooling functions exhibit a decay which resembles that of the function that we adopt. Our cooling schedule hits a temperature value of 1 (this value corresponds to the canonical Metropolis-within-Gibbs sampler) exactly half-
Fig. 1 Pseudo-log-posterior values during the simulated annealing optimisation. The first 1000 iterations are not show for better clarity, since they correspond to a completely random update for the process

way through. We emphasise that the total number of iterations \( K \) is set to a very conservative value, since in our experiments we obtained the same qualitative results also for smaller \( K \) values.

The estimation algorithm is made available through a public code repository associated to this paper (Rastelli 2021).

3 Empirical results

The dataset that we study consists of the probabilities of default for 31 banks across 12 countries, namely Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and the UK based on Thomson Reuters’ structural model. Thomson Reuters evaluates the equity market’s view of credit risk via a proprietary structural default prediction framework. Thomson Reuters produces daily updated estimates of the PD or bankruptcy within one year for more than 35,000 companies in the world, where the PDs are ranked to create 1–100 percentile scores (Pourkhanali et al. 2016). We split it into four time periods which is shown in Table 1.
| Table 1 | Explanation of four different periods in dataset |
|---------|-----------------------------------------------|
| Period  | Start date                     | End date     |
| Pre-crisis | 3/Jan/2005                   | 2/Jan/2008   |
| Financial crisis | 3/Jan/2008                   | 2/Jun/2010   |
| Sovereign crisis | 3/Jun/2010                   | 2/Jan/2013   |
| Post-crisis | 3/Jan/2013                   | 17/Nov/2016  |

| Table 2 | Number of significant partial correlations |
|---------|-------------------------------------------|
| Pre-crisis | 273                                      |
| Financial crisis | 285                                      |
| Sovereign crisis | 271                                      |
| Post-crisis | 241                                      |

3.1 Descriptive statistics

A summary of the values of default probabilities for each bank is provided in Table 16 in Appendix. Banks were also categorised according to their country of origin. The default probabilities for each country were then obtained by averaging the default probability values across the appropriate banks. A summary of these values is provided in Table 17 in Appendix. Figure 2 shows the boxplots for the logarithm of probabilities of default of 31 banks from 2005 to 2016. Due to having long tails, we used $\log(PD)$ to have more visible Boxplots. From these plots, it can be inferred that certain banks are more volatile and that their default probabilities change more drastically. These include Banca Monte dei Paschi di Siena (BMPS), Commerzbank AG and ING Group.

3.2 Partial correlation

To determine the connectedness between the banks during each period, the partial correlation values between bank $i$ and bank $j$ were calculated and tested for significance using the R statistical software. Our naive assumption is that during the financial and sovereign crises, the connections between banks would be closer together. Therefore, we would expect more significant partial correlations during these periods. The table of counts demonstrates that our assumption is true during the financial crisis, but not during the sovereign crisis. However, this result alone is not sufficiently strong as it does not take into account the actual value of the partial correlations.

In order to have a better visual map of ranking changes of banks, Fig. 3 is plotted here. It shows how the PD of banks and financial institutes (eventually ranking of banks) change over subsequent periods.

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3 Results are available upon request.
3.3 CoRisk values

After the calculation of the partial networks, and using the 1-year default probability values for each bank, we are now able to calculate the CoRisk\textsubscript{in} and CoRisk\textsubscript{out} at each point in time. The change in CoRisk values is shown in Fig. 4. To have more clear plots, we split data into two different groups and CoRisk\textsubscript{in} and CoRisk\textsubscript{out} are plotted for each group. These figures exhibit spikes in the CoRisk values during the financial and sovereign crises, confirming that more risk was transmitted during these periods. The CoRisk values after 2012 remain higher than they were before the crises.
Fig. 3 Alluvial diagram illustrating the changes of PD for banks over the four different periods. Bins are labelled as ‘LL’ (low-low), ‘ML’ (medium-low), ‘M’ (medium), ‘MH’ (medium-high) and ‘HH’ (high-high) by default with smaller sudden spikes. This could be due to the lingering effects of the crises and the fact that some banks are yet to stabilise. The \( \text{CoRisk}_{ij} \) matrix was also calculated based on the significant partial correlation matrix obtained earlier for each period.\(^4\)

### 3.4 Minimum spanning tree (MST)

Network models are frequently adopted in the field of financial research due to their effectiveness at visualising large datasets. They have proven to be an effective resource in the prediction of market movements. One of the more popular methods for visualisation of financial networks and building the dependence network is the minimum spanning tree (MST) approach (Mantegna 1999) which is designed to select or filter the information presented in the dependence (or correlation) matrix. The metric distance for creating the edges of a financial network, such as in Wang et al. (2018), uses the partial correlation values, \( C_{ij} \), and is given by the following equation

\[
d_{ij} = \sqrt{2(1 - C_{ij})}.
\]

In our work, we use a different distance metric, replacing the partial correlation values with \( \text{CoRisk} \) values. The formula for the distance between two edges will then be as

\(^4\) Results are available upon request.
follows,

$$d_{ij} = \sqrt{2(1 - \text{CoRisk}_{ij}).}$$  \hfill (8)

**Remark 1** Unlike the partial correlation values, the CoRisk values are not symmetric, that is $d_{ij} \neq d_{ji}$. Since CoRisk takes values from $-\infty$ to 1, $d_{ij}$ would always be positive. Furthermore, a larger CoRisk$_{ij}$ value implies that bank $i$ has a greater impact on bank $j$, and this is represented by a shorter distance.

A directed graph consisting of 31 nodes (31 banks) is then formed using the distances obtained (a pair of directed edges between two banks is only present if the banks are significantly correlated as determined earlier). This directed graph consists of a large number of directed edges and is difficult to visualise. Therefore, we used the R software to obtain a MST with directed edges. The MST from each of the four periods is shown in Figs. 5, 6, 7 and 8.
In this work, we consider MST approach based on Banks and countries, separately. Billio et al. (2018) use a time varying weight matrix, but they specify that it can vary at a time scale lower than the entities in the system which is used. We use a constant weight matrix in this work. When determining a weight matrix, it is important that this matrix reflects any connections between countries. One could argue a spatial weight matrix could fill this role of reflecting connectedness. The most simple form might be a binary weight matrix based on the existence of a neighbouring relationship. The results from this, however, are less than satisfactory, and a matrix that better shows the complex nature of economic relationships was desired. In this research, using European countries, the option of travel distance between capitals or stock market cities seems another option at first glance. Countries closer in distance may be more likely to carry out trade between themselves, linking their stock markets more than those far away. Flavin et al. (2002) note that overlapping business hours tend to increase correlations between countries stock markets. Applying this logic in this dataset, the inverse function of travel distance does not prove a reliable option because, with an
increase in globalisation, it is fair to expect that travel distances will not be an efficient factor in stock market correlations.

**Remark 2** In order to apply MST for Banks, they are colour coded in accordance with their countries and made proportional to the value of their total assets in 2016. For example, Nordea is a Swedish bank coloured in yellow and had a total asset value of €615 billion, while British bank Barclays is coloured in green and had a total asset value of €1213 billion. The length of the edges between 2 banks is proportional to the distance metric used, and the direction shows which bank is transmitting the risk.

Figure 5 shows the MST before the global financial crisis. The Swedish bank SEB is located in the middle of the MST and the other centrally located banks are Commerzbank AG, Danske bank and Credit Agricole. During the financial crisis, the two German banks, Deutsche bank and Commerbank AG, are the centrally located banks in the network, as seen in Fig. 6. The banks also start to cluster according to their country, with the more notable ones being those from the UK and Sweden.
This suggests that the banks within a country become more closely connected during the financial crisis. During the sovereign crisis, from Fig. 7, the clustering effect seems to be less apparent than during the financial crisis. Commerzbank AG remains a centrally located bank, along with Credit Agricole and DNB. Figure 8 shows that the most critically important bank post-crises is BMPS, where due to its high probability of default and financial instability following the 2 crises, it has the largest impact on other European banks.

The above MSTs represent the connections between banks. To determine the relationships between countries instead, MSTs were also plotted by considering the banks located in each country. These MSTs for each of the four periods are shown below.

The UK is the most centrally located country in the financial network before the financial crisis, as seen in Fig. 9. It remains centrally located during the financial crisis (Fig. 10) but the MST divides into two portions separated by the UK, one with Belgium and the other with Norway. During the sovereign crisis (Fig. 11), the major European countries, France, Germany and Italy, became more centrally located. The structure of
the MST remains fairly similar after the sovereign crisis (Fig. 12). In the next section, we analyse MSTs by using two approaches which are called as measures of centrality and fragility.

3.4.1 Analysis of minimum spanning tree using fragility and centrality measures

Fragility, as proposed by Das (2016), is the propensity for risk to spread through a network. This can lead to assess of the speed at which contagion can spread in the system. A network that has more links will transmit more risk as it spreads quicker throughout the network. Therefore, a network with a higher fragility score is more contagious.
Fragility of a network can be described by the following equation, where \( d \) represents the degree of a node in the network,

\[
R = \frac{\mathbb{E}(d^2)}{\mathbb{E}(d)}. \tag{9}
\]

Fragility values were calculated for the bank networks and country networks across the four periods. The results are summarised in the Table 3.

**Remark 3** The fragility score gives us an overview of the transmission risk within the network, but fails to identify the sources of risk. Centrality measures are used to determine the main banks/countries that contribute to the source of the risk.

Below, we introduce some centrality measures used and the centrality scores of both banks and countries are then summarised. The first centrality measure that we use in this work is Betweenness Centrality. Betweenness centrality for a node, \( v \), in a network
Fig. 10 Minimum spanning tree financial crisis by bank

is defined as the number of shortest paths between two nodes that passes through node $v$. It is given by the following formula:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}. \tag{10}$$

A bank with a larger value for its betweenness centrality will be located in a more central location in the network and thus be a major transmitter of risk through the network. Betweenness values were calculated for each period for both the bank and country networks.

The second centrality measure, which is called as closeness centrality, measures the inverse of the sum of distances from a node to all other nodes in a network. A higher closeness value suggests that a node is close to other nodes, (for more detail see Grassi et al. 2010). Banks with a relatively high closeness value would mean that it would require less time for it to transmit risk to other banks in the network as these banks would be ‘closer’ to other banks in terms of the CoRisk metric. The formula for
closeness centrality is given by:

\[
closeness(v) = \frac{1}{\sum_{i \neq v} d_{vi}}.
\]  

(11)

The third centrality measure is Laplacian centrality which calculates the drop in Laplacian energy (sum of squares of eigenvalues in a Laplacian matrix) when a vertex is removed, see Qi and Zhang (2013). It incorporates the weights of the edges in the measure, which makes it a stronger measure than betweenness centrality.

The centroid value is another centrality which measures the number of interactions a node has to determine how central the node is in the network. It can be used to determine which bank is the ‘co-ordinator’ within a network we use LeaderRank. Banks with a relatively high centroid value will play a more central role in the financial network (Scardoni and Laudanna 2012). In order to measure the influence of a node in a directed network, by using a standard random walk procedure, we use LeaderRank. Banks with a higher LeaderRank score are more influential in the financial network.
Tables 4, 5, 6, 7, 8, 9, 10 and 11 show the centrality scores using the 5 aforementioned different measures. Banks/countries that have a significant score are highlighted in bold values. The betweenness centrality measure seems to be the least correlated with the other 4 measures. This is likely due to the fact that it is the only measure that does not account the weights of edges in the financial network. For the bank network pre-crisis, Erste Group bank and UniCredit are the more important banks within the financial network, followed by Banco Popular Espanol, Commerzbank AG and Credit Agricole. These banks are from different countries around Europe but are important financial institutions within their own country. During the financial crisis, the three critical banks are BMPS, Danske bank and ING. This supports the fact that banks from Denmark and Netherlands were one of the worst affected banks during the financial crisis. This would have made them riskier within the financial network, resulting in higher centrality values, especially for measures that rely heavily on edge weights.

During the sovereign crisis, the banks that had the highest centrality scores were BMPS, Banca Popolare di Milano and Basler Kantonalbank. BMPS fell into severe financial trouble in 2012 due to increasing Italian government debt and lost more
Table 3  Fragility score for different periods

| Period          | Bank network | Country network |
|-----------------|--------------|-----------------|
| Pre-crisis      | 40.81        | 16.75           |
| Financial crisis| 40.32        | 16.58           |
| Sovereign crisis| 41.24        | 19.26           |
| Post-crisis     | 43.27        | 18.86           |

Table 4  Centrality Scores for Banks: pre-crisis

| Betweeness | Closeness | Laplacian | Centroid | LeaderRank |
|------------|-----------|-----------|----------|------------|
| BMPS       | 5         | 0.0177    | 3276     | 0.9913     |
| BPM        | 3         | 0.0181    | 3534     | 1.0363     |
| BBVA       | 6         | 0.0161    | 2348     | 0.8110     |
| SAB        | 1         | 0.0181    | 3550     | 0.9136     |
| BPES       | 2         | 0.0191    | 4058     | 1.1265     |
| SAN        | 4         | 0.0172    | 3038     | 0.9462     |
| BCV        | 12        | 0.0186    | 3776     | 0.9136     |
| BARC       | 10        | 0.0177    | 3296     | 0.9136     |
| BSKP       | 0         | 0.0181    | 3490     | 0.9136     |
| BNP        | 11        | 0.0172    | 3026     | 0.9136     |
| CBK        | 39        | 0.0181    | 3522     | 0.9136     |
| ACA        | 36        | 0.0181    | 3510     | 0.9136     |
| CSG        | 15        | 0.0181    | 3498     | 0.9136     |
| DANSKE     | 9         | 0.0168    | 2772     | 0.9136     |
| DBK        | 15        | 0.0172    | 3026     | 0.9136     |
| DNB        | 2         | 0.0168    | 2796     | 0.9136     |
| EBS        | 26        | 0.0196    | 4308     | 1.1715     |
| HSBC       | 0         | 0.0172    | 3074     | 0.9136     |
| ING        | 8         | 0.0186    | 3784     | 0.9136     |
| ISP        | 2         | 0.0177    | 3288     | 0.9136     |
| KBC        | 7         | 0.0191    | 4034     | 1.1265     |
| LLOY       | 11        | 0.0186    | 3748     | 0.9136     |
| LUKN       | 0         | 0.0168    | 2828     | 0.9136     |
| NDA        | 0         | 0.0161    | 2380     | 0.9136     |
| RBS        | 11        | 0.0181    | 3530     | 0.9136     |
| SEB        | 33        | 0.0186    | 3748     | 0.9136     |
| GLE        | 14        | 0.0177    | 3264     | 0.9136     |
| SGKN       | 8         | 0.0172    | 3046     | 0.9136     |
| STAN       | 5         | 0.0164    | 2594     | 0.9136     |
| SWED       | 9         | 0.0172    | 3022     | 0.9136     |
| UCG        | 0         | 0.0196    | 4264     | 1.1715     |
than a billion dollars, and was later involved in a scandal. The large risk associated with BMPS resulted in higher CoRisk values, which caused the bank to be a more central node in the financial network. BPM was also hit hard during the sovereign crisis and had large CoRisk values. These two banks continued to have difficulty after the sovereign crisis, and have the highest centrality scores for that period too. For the country network pre-crisis, the UK and France were the most important countries in the European financial network. When the financial crisis hit, Norway and Belgium became the more centrally located nodes in the network. Belgium was one of the

| Bank | Centrality Scores for Banks: financial crisis |
|------|---------------------------------------------|
|      | Betweeness | Closeness | Laplacian | Centroid | LeaderRank |
| BMPS | 10         | 0.0202    | 4510      | -3       | 1.2382     |
| BPM  | 1          | 0.0158    | 2162      | -13      | 0.7796     |
| BBVA | 2          | 0.0169    | 2804      | -13      | 0.9172     |
| SAB  | 2          | 0.0165    | 2606      | -11      | 0.8713     |
| BPES | 3          | 0.0177    | 3256      | -13      | 1.0089     |
| SAN  | 1          | 0.0182    | 3434      | -11      | 1.0547     |
| BCV  | 0          | 0.0161    | 2384      | -15      | 0.8254     |
| BARC | 11         | 0.0169    | 2760      | -13      | 0.9172     |
| BSKP | 0          | 0.0154    | 1968      | -15      | 0.7337     |
| BNP  | 7          | 0.0197    | 4216      | -5       | 1.1923     |
| CBK  | 38         | 0.0177    | 3280      | -5       | 1.0089     |
| ACA  | 15         | 0.0177    | 3236      | -9       | 1.0089     |
| CSG  | 3          | 0.0169    | 2816      | -9       | 0.9172     |
| DANSKE | 31      | 0.0202    | 4506      | -3       | 1.2382     |
| DBK  | 16         | 0.0182    | 3494      | -7       | 1.0547     |
| DNB  | 6          | 0.0182    | 3482      | -9       | 1.0547     |
| EBS  | 11         | 0.0173    | 2986      | -7       | 0.9630     |
| HSBC | 3          | 0.0173    | 3066      | -7       | 0.9630     |
| ING  | 20         | 0.0202    | 4506      | -3       | 1.2382     |
| ISP  | 5          | 0.0186    | 3764      | -5       | 1.1006     |
| KBC  | 9          | 0.0173    | 3078      | -9       | 0.9630     |
| LLOY | 32         | 0.0182    | 3498      | -9       | 1.0547     |
| LUKN | 2          | 0.0182    | 3482      | -9       | 1.0547     |
| NDA  | 2          | 0.0181    | 3494      | -5       | 1.0547     |
| RBS  | 36         | 0.0182    | 3494      | -11      | 1.0547     |
| SEB  | 7          | 0.0169    | 2808      | -11      | 0.9172     |
| GLE  | 18         | 0.0173    | 3006      | -9       | 0.9630     |
| SGKN | 1          | 0.0177    | 3232      | -7       | 1.0089     |
| STAN | 0          | 0.0177    | 3268      | -11      | 1.0089     |
| SWED | 18         | 0.0165    | 2610      | -7       | 0.8713     |
| UCG  | 6          | 0.0173    | 3046      | -9       | 0.9630     |
Table 6 Centrality Scores for Banks: sovereign crisis

| Bank | Betweenness | Closeness | Laplacian | Centroid | LeaderRank |
|------|-------------|-----------|-----------|----------|------------|
| BMPS | 27          | 0.0197    | 4284      | −3       | 1.1681     |
| BPM  | 25          | 0.0197    | 4296      | −5       | 1.1681     |
| BBVA | 7           | 0.0169    | 2792      | −15      | 0.8986     |
| SAB  | 2           | 0.0186    | 3756      | −7       | 1.0783     |
| BPES | 6           | 0.0181    | 3562      | −9       | 1.0333     |
| SAN  | 3           | 0.0161    | 2384      | −15      | 0.8087     |
| BCV  | 1           | 0.0181    | 3542      | −9       | 1.0333     |
| BARC | 12          | 0.0173    | 3082      | −11      | 0.9435     |
| BSKP | 3           | 0.0202    | 4578      | −9       | 1.2130     |
| BNP  | 21          | 0.0186    | 3808      | −7       | 1.0783     |
| CBK  | 48          | 0.0192    | 4066      | 0        | 1.1232     |
| ACA  | 19          | 0.0182    | 3578      | −7       | 1.0333     |
| CSG  | 18          | 0.0186    | 3764      | −7       | 1.0783     |
| DANSKE | 3     | 0.0165    | 2574      | −13      | 0.8536     |
| DBK  | 1           | 0.0173    | 3046      | −11      | 0.9435     |
| DNB  | 6           | 0.0191    | 4046      | −3       | 1.1232     |
| EBS  | 21          | 0.0186    | 3808      | −7       | 1.0783     |
| HSBC | 0           | 0.0177    | 3292      | −11      | 0.9884     |
| ING  | 1           | 0.0181    | 3562      | −7       | 1.0333     |
| ISP  | 3           | 0.0181    | 3586      | −15      | 1.0333     |
| KBC  | 3           | 0.0165    | 2606      | −15      | 0.8536     |
| LLOY | 20          | 0.0173    | 3074      | −9       | 0.9435     |
| LUKN | 1           | 0.0191    | 4070      | −9       | 1.1232     |
| NDA  | 2           | 0.0165    | 2598      | −11      | 0.8536     |
| RBS  | 12          | 0.0169    | 2880      | −11      | 0.8985     |
| SEB  | 1           | 0.0161    | 2352      | −15      | 0.8087     |
| GLE  | 11          | 0.0191    | 4010      | −9       | 1.1232     |
| SGKN | 2           | 0.0165    | 2594      | −13      | 0.8536     |
| STAN | 0           | 0.0157    | 2174      | −17      | 0.7638     |
| SWED | 3           | 0.0191    | 4058      | −3       | 1.1232     |
| UCG  | 20          | 0.0173    | 3018      | −9       | 0.9435     |

European states most affected by the financial crisis, resulting in a higher CoRisk value between other countries. Norway, on the other hand, was not hugely affected by the financial crisis. The impact on Norway is therefore more likely to be due to its high connectedness with other European economies. Germany and the UK became the countries with the highest centrality scores during the sovereign crisis. These two countries are the largest economies in Europe, and the driving force of the European economy as a whole during the sovereign crisis. In post-crises, Italy becomes the most
Table 7 Centrality Scores for Banks: post-crisis

|          | Betweeness | Closeness | Laplacian | Centroid | LeaderRank |
|----------|------------|-----------|-----------|----------|------------|
| BMPS     | 73         | 0.0208    | 4908      | 0        | 1.2056     |
| BPM      | 12         | 0.0208    | 4972      | −5       | 1.2056     |
| BBVA     | 5          | 0.0196    | 4396      | −11      | 1.1194     |
| SAB      | 6          | 0.0168    | 2940      | −9       | 0.8611     |
| BPES     | 25         | 0.0202    | 4702      | −9       | 1.1625     |
| SAN      | 3          | 0.0186    | 3876      | −9       | 1.0333     |
| BCV      | 1          | 0.0202    | 4662      | −3       | 1.1625     |
| BARC     | 1          | 0.0165    | 2674      | −15      | 0.8181     |
| BSKP     | 0          | 0.0177    | 3368      | −11      | 0.9472     |
| BNP      | 1          | 0.0186    | 3852      | −9       | 1.0333     |
| CBK      | 6          | 0.0161    | 2416      | −13      | 0.7750     |
| ACA      | 3          | 0.0173    | 3206      | −11      | 0.9042     |
| CSG      | 3          | 0.0165    | 2698      | −17      | 0.8181     |
| DANSKE   | 2          | 0.0202    | 4650      | −7       | 1.1625     |
| DBK      | 25         | 0.0186    | 3868      | −9       | 1.0333     |
| DNB      | 0          | 0.0173    | 3146      | −13      | 0.9042     |
| EBS      | 4          | 0.0173    | 3134      | −13      | 0.9042     |
| HSBC     | 0          | 0.0186    | 3888      | −9       | 1.0333     |
| ING      | 5          | 0.0196    | 4384      | −9       | 1.1194     |
| ISP      | 3          | 0.0161    | 2472      | −17      | 0.7750     |
| KBC      | 6          | 0.0168    | 2888      | −13      | 0.8611     |
| LLOY     | 9          | 0.0177    | 3424      | −11      | 0.9472     |
| LUKKN    | 0          | 0.0191    | 4150      | −9       | 1.0764     |
| NDA      | 1          | 0.0177    | 3364      | −11      | 0.9472     |
| RBS      | 5          | 0.0181    | 3658      | −11      | 0.9903     |
| SEB      | 0          | 0.0186    | 3876      | −7       | 1.0333     |
| GLE      | 14         | 0.0186    | 3944      | −5       | 1.0333     |
| SGKN     | 0          | 0.0177    | 3408      | −17      | 0.9472     |
| STAN     | 13         | 0.0202    | 4702      | −5       | 1.1625     |
| SWED     | 3          | 0.0173    | 3174      | −7       | 0.9042     |
| UCG      | 43         | 0.0197    | 4404      | −3       | 1.1194     |

Central country in the network due to the failure of its banking system as explained above (BMPS and BPM being contributors to the overall risk).

3.4.2 Directed acyclic graph: topological sort

A directed minimum spanning tree is also a directed acyclic graph, allowing us to do a causal analysis on the 8 graphs we had obtained earlier. The aim of this was to see which banks and countries transmitted the most risk (source nodes) to other
Table 8  Centrality scores for countries: pre-crisis

| Country     | Betweenness | Closeness | Laplacian | Centroid | LeaderRank |
|-------------|-------------|-----------|-----------|----------|------------|
| Italy       | 4           | 0.0544    | 642       | -4       | 1.1000     |
| Spain       | 1           | 0.0471    | 450       | -6       | 0.9000     |
| Switzerland | 5           | 0.0544    | 650       | -4       | 1.1000     |
| UK          | 6           | 0.0589    | 740       | 0        | 1.2000     |
| France      | 2           | 0.0589    | 744       | -2       | 1.2000     |
| Germany     | 1           | 0.0442    | 360       | -4       | 0.8000     |
| Denmark     | 1           | 0.0505    | 544       | -2       | 1.0000     |
| Norway      | 2           | 0.0416    | 274       | -8       | 0.7000     |
| Austria     | 0           | 0.0416    | 294       | -6       | 0.7000     |
| Netherlands | 2           | 0.0544    | 638       | -2       | 1.1000     |
| Belgium     | 11          | 0.0544    | 642       | -4       | 1.1000     |
| Sweden      | 1           | 0.0544    | 646       | -4       | 1.1000     |

Table 9  Centrality scores for countries: financial crisis

| Country     | Betweenness | Closeness | Laplacian | Centroid | LeaderRank |
|-------------|-------------|-----------|-----------|----------|------------|
| Italy       | 5           | 0.0473    | 434       | -2       | 0.9000     |
| Spain       | 0           | 0.0544    | 642       | -4       | 1.1000     |
| Switzerland | 0           | 0.0472    | 450       | -4       | 0.9000     |
| UK          | 1           | 0.0506    | 548       | -2       | 1.0000     |
| France      | 3           | 0.0507    | 532       | -4       | 1.0000     |
| Germany     | 2           | 0.0507    | 552       | -4       | 1.0000     |
| Denmark     | 6           | 0.0545    | 634       | -6       | 1.1000     |
| Norway      | 3           | 0.0590    | 748       | -2       | 1.2000     |
| Austria     | 3           | 0.0506    | 524       | -4       | 1.0000     |
| Netherlands | 2           | 0.0394    | 200       | -8       | 0.6000     |
| Belgium     | 11          | 0.0590    | 748       | -2       | 1.2000     |
| Sweden      | 0           | 0.0506    | 548       | -2       | 1.0000     |

nodes in the financial network. The key banks/countries for each period are shown below. These banks/countries are not necessarily the same as those with high centrality scores. Instead, they are financial institutions with a high importance in the European economy. For instance, Credit Agricole and Commerzbank represent the key roles played by France and Germany, which are considered as leaders of the European economy as a whole. Key banks and countries transmitted the most risks for each period are shown in Table 12.
### Table 10  Centrality scores for countries: sovereign crisis

| Country    | Betweeness | Closeness | Laplacian | Centroid | LeaderRank |
|------------|------------|-----------|-----------|----------|------------|
| Italy      | 4          | 0.0590    | 800       | 0        | 1.0435     |
| Spain      | 0          | 0.0589    | 808       | −6       | 1.0435     |
| Switzerland| 0          | 0.0472    | 494       | −6       | 0.7826     |
| UK         | 1          | 0.0643    | 918       | −2       | 1.1304     |
| France     | 3          | 0.0590    | 804       | −2       | 1.0435     |
| Germany    | 7          | 0.0644    | 918       | 0        | 1.1304     |
| Denmark    | 0          | 0.0544    | 694       | −4       | 0.9565     |
| Norway     | 0          | 0.0544    | 694       | −4       | 0.9565     |
| Austria    | 2          | 0.0506    | 592       | −4       | 0.8696     |
| Netherlands| 0          | 0.0545    | 698       | −4       | 0.9565     |
| Belgium    | 1          | 0.0590    | 796       | −6       | 1.0435     |
| Sweden     | 0          | 0.0590    | 796       | −6       | 1.0435     |

### Table 11  Centrality scores for countries: post-crisis

| Country    | Betweeness | Closeness | Laplacian | Centroid | LeaderRank |
|------------|------------|-----------|-----------|----------|------------|
| Italy      | 6          | 0.0643    | 910       | −2       | 1.1471     |
| Spain      | 2          | 0.0544    | 682       | −4       | 0.9706     |
| Switzerland| 1          | 0.0544    | 686       | −4       | 0.9706     |
| UK         | 3          | 0.0643    | 910       | −2       | 1.1471     |
| France     | 4          | 0.0590    | 792       | −2       | 1.0588     |
| Germany    | 4          | 0.0506    | 580       | −2       | 0.8824     |
| Denmark    | 0          | 0.0505    | 580       | −6       | 0.8824     |
| Norway     | 0          | 0.0589    | 792       | −4       | 1.0588     |
| Austria    | 0          | 0.0544    | 686       | −4       | 0.9706     |
| Netherlands| 0          | 0.0544    | 682       | −6       | 0.9706     |
| Belgium    | 0          | 0.0544    | 686       | −6       | 0.9706     |
| Sweden     | 0          | 0.0544    | 686       | −4       | 0.9706     |

### Table 12  Key banks and countries which transmitted the most risks

| Pre-crisis | Financial crisis | Sovereign crisis | Post-crisis |
|------------|------------------|------------------|-------------|
| Banque Cantonale Vaudoise | Commerzbank | Banco Popular Espanol | BMPS |
| Barclays | Credit Suisse | Commerzbank | Banco Popular Espanol |
| Commerzbank | ING | Credit Agricole | Barclays |
| Credit Agricole | RBS | ING | Commerzbank |

| Key countries transmitted most risk |
|-----------------------------------|
| France | France | France | Italy |
| Germany | Germany | Germany | |

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3.4.3 Evolution of country financial network

MSTs are not the only method of visualising the results of our analysis. Since there are only 12 countries in our study, we could analyse the complete graph to see the evolution of risk transmission during the crisis periods. Below are four such graphs, where the size of the node represents the Laplacian Centrality score and the width of the edges represents the net CoRisk (sum of $\text{CoRisk}_{in}$ and $\text{CoRisk}_{out}$) between two countries. We can see that net CoRisk significantly increased from pre-crisis to financial crisis and slightly reduced during the sovereign crisis. However, it remained at a relatively higher level in the post-crisis period when compared with pre-crisis. The increased node sizes over time also revealed an interesting pattern about increased Laplacian Centrality (level of influence in the network) (Figs. 13, 14).

3.5 Latent position model empirical results

The main information that we obtain from our fitted LPM model is the latent positions of all financial institution in each of the periods. We show these latent spaces in Figs. 15 and 16, by comparing them with the corresponding country and probability of default, respectively.

Since not all the available information can be shown in these plots, we have also included additional outputs in our public code repository (Rastelli 2021). In Fig. 15, the countries and probabilities of default of the financial institutions are highlighted within the latent space. Before the crises, the points tend to be close to each other, signalling a dense status of the system, whereby risk may be easily spread. We note that two Swiss banks are not shown in the plot since they are located far from the other institutions, and that they also show a low default probability in all time periods.

Starting from the second time period (which corresponds to the 2008 financial crisis), we observe that the latent visualisation expands and creates clusters in the space. The expansion can be interpreted as a measure to counteract risk from partners, and reduce the overall correlation. Regarding the presence of clusters, our interpretation is rather straightforward: clustered institutions tend to be close to each other and will tend to be more contagious towards one another. As a consequence, they are more likely to exhibit similar default probabilities. By contrast, we expect less contagiousness between clusters, especially if they are located far apart.

Remark 4 It is important to note that these clusters highlight some associations between banks that may play a crucial role within the financial system. These associations can help in identifying key institutions that can pose systemic risk concerns, but, also, they may help in understanding the dynamics of the spread of debt.

We note a tendency to create assortative behaviour with respect to the countries, intended as the fact that banks of the same country are close to each other and thus share higher risks. The Spanish, Swedish and Italian banks (separately) seem to exhibit very similar behaviour throughout the period. The Swiss banks are located in the outskirts of the latent space and seem to be not particularly influenced by the other institutions, throughout the study. Many associations that are exhibited in these plots are not related...
Fig. 13 Upper figure shows pre-crisis and bottom plot report network in financial crisis
Fig. 14  Upper figure shows sovereign crisis, while the bottom plot shows network in post-crisis
In Fig. 15, we highlight the dynamic nature of our model. Both the colours and size of the points describe the default probability associated to the bank. Also, we include two oriented segments to highlight the position changes with respect to the previous and following time frames. This plot highlights that the banks with a higher default probability tend to be located near the centre and the lower regions of the space. The model provides an interesting view on the dynamics for the bank BMPS, which starts from a central position, but then drifts away from all other banks while increasing its probability of default. This is clearly in agreement with the idiosyncratic nature of the financial distress experienced by this bank during the period.

3.5.1 A measure of systemic risk derived from the LPM

We use our inferred LPM to derive a measure of risk associated to each of the financial institutions. Since we are interested in the part of risk that is received from the system,
we can use the respective latent positions of all pairs of institutions to derive an interpretable quantity. In the LPM view, the two necessary conditions for two institutions to affect each other are:

1. the institutions are joined with an edge;
2. the institutions are close in the latent space.

As a consequence, we propose to calculate, for each institution, the inverse of the average Euclidean distance from its neighbours. This index will be very high when the neighbours are on average very close, signalling that the banks will affect each other to a high degree. By contrast, a low value of this index will indicate that the neighbours are not located close to the bank, so they cannot have much of an influence on it. Figure 17 shows the banks in all time periods highlighting their measured systemic risk level. Clearly, banks at higher risk are those located close to the centre of the space, and those that have several other banks nearby. The institutions located in the outskirts of the space exhibit low risk. We refer the reader to the supplementary materials that are
available from our repository (Rastelli 2021) for more information regarding specific banks.

From a more global perspective, we summarise the same information using boxplots in Fig. 18. This figure shows the distribution of the risk measure across time, signalling a clear decrease in systemic risk over time. This can be interpreted as the model signalling a general tendency towards better financial stability.

### 3.5.2 Comparison between LPM risk and CoRisk

Both CoRisk and the LPM risk measure are derived from the partial correlations; however, it is unclear whether these measures are equivalent or if they provide different perspectives on systemic risk. In Table 13, we compare the two measures for the risk in the pre-crises and post-crises time frames. The highest 5 values of each column are highlighted in bold to emphasise which banks were considered at most risk, for each measure.
Fig. 18 The boxplots represent the distribution of the measure of systemic risk across all the financial institutions in each of the time frames.

Table 13 Comparison between LPM risk and CoRisk\textsubscript{In} and CoRisk\textsubscript{Out}, in the first and last time frames (pre-crises and post-crises, respectively). The highest 5 values of each column are highlighted in red to identify the banks at most risk for each criteria.

| Bank | Pre-crises | Post-crises |
|------|------------|-------------|
|      | LPM CoRisk\textsubscript{In} | CoRiskOut | LPM CoRisk\textsubscript{In} | CoRiskOut |
| BMPS | 0.83 | 0.00 | 0.02 | 0.17 | 0.38 | 1.31 |
| BPM  | 0.79 | 0.01 | 0.03 | 0.31 | 0.62 | 0.43 |
| BBVA | 0.46 | 0.04 | 0.03 | 0.55 | -0.24 | 0.21 |
| SAB  | 0.46 | 0.05 | 0.03 | 0.35 | 2.35 | 0.71 |
| BPES | 0.43 | -0.00 | 0.01 | 0.35 | 0.22 | 0.33 |
| SAN  | 0.46 | -0.01 | 0.04 | 0.52 | -0.83 | 0.40 |
| BCV  | 0.42 | 0.10 | 0.06 | 0.14 | 0.37 | 0.01 |
| BARC | 0.90 | 0.08 | 0.07 | 0.32 | -0.18 | 0.34 |
| BNP  | 0.88 | 0.03 | 0.06 | 0.36 | 0.07 | 0.25 |
| CBK  | 0.45 | 0.07 | 0.24 | 0.27 | -0.72 | 1.03 |
| ACA  | 0.52 | 0.09 | 0.10 | 0.35 | 0.04 | 0.39 |
| CSG  | 0.66 | 0.06 | 0.11 | 0.27 | 0.74 | 0.76 |
| DANSKE | 0.76 | 0.10 | 0.05 | 0.32 | -0.41 | 0.15 |
| DBK  | 0.91 | 0.16 | 0.14 | 0.42 | 2.68 | 1.47 |
| DNB  | 0.71 | 0.10 | 0.05 | 0.41 | 0.39 | 0.13 |
| EBS  | 0.71 | 0.06 | 0.16 | 0.35 | 0.98 | 0.51 |
Table 13 continued

| Bank | Pre-crises | Post-crises |
|------|------------|-------------|
|      | LPM        | CoRiskIn    | CoRiskOut   |
|      |            | LPM         | CoRiskIn    | CoRiskOut   |
| HSBC | 0.46       | 0.05        | 0.02        | 0.34        | 1.25        | 0.10        |
| ING  | 0.74       | 0.04        | 0.08        | **0.43**    | 0.21        | 0.26        |
| ISP  | 0.47       | 0.10        | 0.04        | **0.45**    | **1.53**    | 0.46        |
| KBC  | 0.68       | **0.11**    | 0.04        | 0.42        | 0.11        | 0.16        |
| LLOY | 0.76       | 0.10        | 0.06        | 0.41        | 0.30        | 0.25        |
| NDA  | 0.35       | **0.11**    | 0.01        | 0.25        | **1.15**    | 0.13        |
| BSKP | 0.69       | 0.01        | 0.08        | 0.30        | −0.01       | **0.78**    |
| SEB  | **0.92**   | **0.11**    | 0.10        | 0.32        | −0.27       | 0.16        |
| GLE  | 0.78       | 0.07        | 0.07        | 0.35        | 0.48        | 0.41        |
| SGKN | 0.47       | 0.10        | 0.03        | 0.16        | −0.37       | 0.03        |
| STAN | 0.68       | 0.05        | 0.04        | 0.41        | 1.07        | 0.46        |
| SWED | 0.82       | 0.08        | 0.10        | 0.25        | 0.86        | 0.10        |
| UCG  | 0.79       | 0.05        | 0.04        | 0.35        | 0.82        | **1.15**    |

Fig. 19 Comparison between the average LPM risk and the risk implied by CoRisk

In addition, Fig. 19 provides a visual representation of the average LPM risk against the average \( \text{CoRisk}_{\text{in}} \) and \( \text{CoRisk}_{\text{out}} \) measures, where the average is calculated across the 4 time frames. In this figure, we clearly notice that the two approaches produce different perspectives on risk; however, there is some good agreement between the LPM risk and the \( \text{CoRisk}_{\text{out}} \).

3.6 Other risk measures

To evaluate performance of proposed method, we consider three different systemic risk measures as, namely CoVaR. \( \Delta \text{CoVaR} \), volatility and a macro-control variable as a credit spread (CRESPIR). Then, we divided each sample into two sub-samples, which we subsequently denote as the in-sample and out-of-sample. The in-sample and out-
of-sample periods of the dataset are respectively, from January 2005 to March 2015 and from April 2015 to October 2016. Moreover, to compare and show robustness of our systemic risk measure with other measures in the current literature we consider four different logit regression models as

Model (1):
\[ Y_t = F(\alpha_0 + \beta_0 X_t + \gamma_0 Z_t), \]  
(12)

Model (2):
\[ Y_t = F(\alpha_0 + \beta_0 X_t + \beta_1 X_{t-1} + \gamma_0 Z_t), \]  
(13)

Model (3):
\[ Y_t = F(\alpha_0 + \alpha_1 Y_{t-1} + \beta X_t + \gamma_0 Z_t), \]  
(14)

Model (4):
\[ Y_t = F(\alpha_0 + \alpha_1 Y_{t-1} + \beta_0 X_t + \beta_1 X_{t-1} + \gamma_0 Z_t), \]  
(15)

where \( Y_t \) is a binary variable which takes value of 1 in crisis and critical economic situations, and 0 other times, \( X_t \) is systemic risk measure, and \( Z_t \) is macroeconomic controller variable. Note that for the sake of consistency, we consider lag variables for different scenarios in 13–15.

In this work, we use a logit model instead of a probit model since Hasse (2020a) specified that considering the low ratio of instances of 1 to instances of 0 exhibited by the recession dummy, logit models are preferable to probit models (See also Naceur et al. 2019). For this reason, we fitted logit regression models (Hasse and Lajaunie 2020; Hasse 2020a by using the R package EWS Hasse et al. 2021) to each sub-sample, and estimation results are presented in Table 14. Results are obtained from different logit regression models 12 to 15. Table 14 provides evidence of the usefulness of our systemic risk measure. Our empirical evidence is robust to the introduction of macro-control variable, and our measure of systemic risk exhibits interesting results compared to other measures. Regarding the Akaike information criterion (AIC), it demonstrates that the best specification is CoRisk model among others. Further, three systemic measures of CoRisk, CoVaR (Tobias and Brunnermeier 2016) and volatility have positive coefficients while \( \Delta \text{CoVaR} \) has negative one, where CoRisk variables are more significant to compare other risk measures which shows that it contains more information than other risk variables. In this work, the macro-control variable is extracted from OECD databases, for the period from 2005 to 2016.

Thus, we conclude that our systemic risk measure could be used as an early warning sign that is positively and significantly associated macroeconomic downturns. Now main question is whether these risk measures which represented in Table 14 and computed by using R package SystemicR by Hasse (2020b), are informative and consistence about the future economic shocks. To explore this question and analysis performance of proposed model, we use R package forecast (Hyndman et al. 2020) and based on state space models (Hyndman et al. 2008), we compute forecasting of all risk measures of CoRisk, CoRisk, CoVaR, volatility macro-control of CRESPR. Then based on best fit of logit regression which reported in Table 14, we evaluate the ability of systemic risk measures to forecast possible economic shocks. In order to measure the accuracy of forecasts, we use the criterion of mean square error (MSE), and
Table 14  Early warning signal: an application of the systemic risk measure. Labels ***, ** and * represents significance at 99%, 95% and 90% levels, respectively. Results are computed using RStudio version 1.4.1717 and packages EWS (Hasse et al. 2021) and aod (Lesnoff et al. 2010). Standard errors are reported in parentheses below the estimates.

| Model | (1) | (2) | (3) | (4) |
|-------|-----|-----|-----|-----|
| Intercept | 11.798 | −3.906 | 1.140 | 21.713*** |
| | (6.586) | (3.009) | (1.276) | (4.727) |
| $Y_{t-1}$ | 5.860*** | 6.361*** | (1.232) | (1.492) |
| $X_{t-1}$ | −3.985** | 2.270* | (1.379) | (1.029) |

**Systemic risk measures**

| ΔCoVaR | −5.740* | (2.346) |
| CoRisk | 5.414** | (1.737) |
| Volatility | 33.039* | (13.237) |
| CoVaR | 2.469* | (1.031) |

**Macro-control variable**

| CRES PR | −1.323* | −0.007 | −0.208* | −2.018*** |
| | (0.581) | (0.195) | (0.095) | (0.420) |

**Data**

| Frequency | Monthly | Monthly | Monthly | Monthly |
| Observation | 124 | 124 | 124 | 124 |
| AIC | 49.662 | 48.288 | 109.96 | 98.295 |

Table 15  Loss functions based on different risk measures for out-of-sample which start from April 2015 to October 2016

| Risk measures | Loss functions (error measures) |
|---------------|---------------------------------|
|              | MSE    | MAE    | LogLoss |
| CoRisk        | 0.0006 | 0.0240 | 0.0243 |
| CoVaR         | 0.0196 | 0.0856 | 0.0987 |
| ΔCoVaR        | 0.0066 | 0.0590 | 0.0627 |
| Volatility    | 0.0132 | 0.0597 | 0.0692 |

mean absolute error (MAE) and LogLoss, loss functions. Table 15 shows forecasting performance of proposed model via other benchmarks.

5 LogLoss function computes cross-entropy loss between forecasting and true values of out-of-sample. It is available in R package MLmetrics (Yan 2016).
4 Conclusions

The recent crises have changed drastically the structure of the European financial system. While the 2008 financial crisis has hit globally, the sovereign crisis has had a more lasting impact on certain European banks. We have adopted a number of descriptive measures and model-based measures to obtain a new and different perspective on the European financial system. The CoRisk measure allowed us to see which banks and countries were more systemically important within the financial network during the financial and sovereign crises. In particular, we have disentangled the different driving forces of risk using the connectedness and the default probabilities. The combination of the visualisation tools and of the centrality measures was able to identify the main sources of the risk. Our methodological framework could be helpful to propose systemic banks rankings. The proposed framework could also be extended to build composite systemic risk index to monitor financial stability. Regarding our latent space model, the results show that the banks expanded in the latent space during the crisis, presumably responding to the onset of the 2008 financial crisis. The model signals a general trend towards financial stability whereby the risk from other institutions remains contained. In fact, after 2008, the latent point process exhibits a more sparse and clustered structure, which is known to be more resilient to targeted attacks or defaults. The latent space approach also enabled us to isolate and measure the risk caused by the financial system, thus introducing a new index for systemic risk and providing additional evidence for the trend towards financial stability.

Regarding possible extensions of our work, we point out that the heuristic simulated annealing was used because of its speed and theoretical guarantees; however, other approaches may be viable. In the Bayesian setting, one may design a sampler to obtain approximate draws from the posterior of the distribution of interest. This would also permit an assessment of the uncertainty associated to the positioning of the nodes in the latent space. In addition, our proposed solution can be implemented on a variety of financial decision-making platforms, enabling individual users to map complex financial systems and make better data-driven financial decisions.

Declarations

Conflict of interest None of the authors has any conflicts of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Appendices

Appendix A: Proof of Proposition 1

Proof We wish to study the density \( \pi \left( y_{(i,t)}^{(t)} | y_{-(i,t)}, Z, X \right) \), up to a proportionality constant that does not depend on \( y_{(i,t)}^{(t)} \):
\[
\pi \left( y_i^{(t)} | y_{-(i,t)}, \mathbf{Z}, \mathbf{X} \right) = \pi \left( \frac{y_i^{(t)}}{\mathbf{Z}, \mathbf{X}} \right) \propto f \left( \frac{y_i^{(t)}}{\mathbf{Z}, \mathbf{X}} \right)
\]

\[
\propto \exp \left\{ -\frac{1}{2} \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij}^{(t)} \eta_{ij} \left( y_i^{(t)} - y_j^{(t)} \right)^2 \right\}
\]

\[
\propto \exp \left\{ -\frac{1}{2} \sum_{j=1, j \neq i}^{N} x_{ij}^{(t)} \eta_{ij} \left( y_i^{(t)} - y_j^{(t)} \right)^2 \right\}
\]

\[
\propto \exp \left\{ -\frac{1}{2} \left[ A_i^{(t)} \left( y_i^{(t)} \right)^2 - 2B_i^{(t)} y_i^{(t)} \right] \right\}
\]

where

\[
A_i^{(t)} = \sum_{j=1, j \neq i}^{N} x_{ij}^{(t)} \eta_{ij},
\]

\[
B_i^{(t)} = \sum_{j=1, j \neq i}^{N} x_{ij}^{(t)} \eta_{ij} y_j^{(t)}.
\]

Then:

\[
\pi \left( y_i^{(t)} | y_{-(i,t)}, \mathbf{Z}, \mathbf{X} \right) \propto \exp \left\{ -\frac{1}{2} \left[ A_i^{(t)} \left( y_i^{(t)} \right)^2 - 2B_i^{(t)} y_i^{(t)} \right] \right\}
\]

\[
\propto \exp \left\{ -\frac{A_i^{(t)}}{2} \left[ \left( y_i^{(t)} \right)^2 - 2 \frac{B_i^{(t)}}{A_i^{(t)}} y_i^{(t)} + \left( \frac{B_i^{(t)}}{A_i^{(t)}} \right)^2 \right] \right\}
\]

\[
\propto \exp \left\{ -\frac{A_i^{(t)}}{2} \left[ y_i^{(t)} - \frac{B_i^{(t)}}{A_i^{(t)}} \right]^2 \right\}
\]

which is proportional to a Gaussian density with the following mean and variance:

\[
\mu_i^{(t)} = \frac{B_i^{(t)}}{A_i^{(t)}}, \quad \nu_i^{(t)} = \frac{1}{A_i^{(t)}}.
\]
Appendix B: Summary of default probabilities by bank

See Tables 16 and 17.

| Bank Name | Mean (%) | SD (%) | Maximum (%) | Minimum (%) | Skewness | Kurtosis |
|-----------|----------|--------|-------------|-------------|----------|----------|
| Banca Monte dei Paschi di Siena (BMPS) | 1.83 | 2.54 | 18.93 | 0.04 | 2.46 | 7.39 |
| Banca Popolare di Milano (BPM) | 0.77 | 0.88 | 4.6 | 0.03 | 1.66 | 2.24 |
| Banco Bilbao Vizcaya (BBVA) | 0.36 | 0.43 | 3.29 | 0.02 | 2.79 | 10.06 |
| Banco de Sabadell (SAB) | 0.35 | 0.31 | 1.51 | 0.01 | 1.11 | 1 |
| Banco Popular Espanol S.A (BPES) | 0.79 | 1.02 | 4.65 | 0 | 1.89 | 2.73 |
| Banco Santander (SAN) | 0.36 | 0.44 | 3.16 | 0.02 | 2.56 | 7.75 |
| Banque Cantonale Vaudoise (BCV) | 0.1 | 0.14 | 0.74 | 0.01 | 2.38 | 5.23 |
| Barclays (BARC) | 1.04 | 1.53 | 16.97 | 0.04 | 3.56 | 17.68 |
| Basler Kantonalbank (BSKP) | 0.08 | 0.15 | 0.98 | 0 | 2.29 | 4.84 |
| BNP Paribas (BNP) | 0.57 | 0.76 | 5.41 | 0.02 | 2.69 | 8.24 |
| Commerzbank AG (CBK) | 2.03 | 3.1 | 23.37 | 0.09 | 3.03 | 10.98 |
| Credit Agricole (ACA) | 1.1 | 1.41 | 7.78 | 0.04 | 1.99 | 3.63 |
| Credit Suisse Group (CSG) | 0.83 | 0.98 | 4.91 | 0.05 | 1.77 | 2.7 |
| Danske Bank (DANSKE) | 0.78 | 1.71 | 16.21 | 0.01 | 4.47 | 24.12 |
| Deutsche Bank (DBK) | 1 | 1.52 | 10.73 | 0.04 | 3.14 | 11.22 |
| DNB ASA (DNB) | 0.54 | 1.13 | 9.11 | 0.03 | 3.93 | 15.93 |
| Erste Group Bank AG (EBS) | 0.93 | 1.39 | 9.4 | 0.06 | 2.73 | 8.07 |
| HSBC | 0.2 | 0.33 | 2.91 | 0.01 | 3.82 | 17.08 |
| ING group (ING) | 1.12 | 2.15 | 21.55 | 0.04 | 3.99 | 20.3 |
| Intesa Sanpaolo (ISP) | 0.53 | 0.63 | 3.59 | 0.02 | 1.63 | 2.06 |
| KBC Bancassurance Holding S.A. (KBC) | 1.17 | 2.09 | 14.73 | 0.02 | 2.8 | 8.27 |
| Lloyds Banking Group (LLOY) | 1.26 | 2.09 | 16.04 | 0.03 | 2.7 | 8.95 |
| Luzerner Kantonalbank (LUKN) | 0.01 | 0.01 | 0.06 | 0 | 2.6 | 7.39 |
| Nordea (NDA) | 0.17 | 0.21 | 1.51 | 0 | 2.57 | 9.26 |
Table 16 continued

| Bank Name                        | Mean (%) | SD (%) | Maximum (%) | Minimum (%) | Skewness | Kurtosis |
|----------------------------------|----------|--------|-------------|-------------|----------|----------|
| Royal Bank of Scotland (RBS)    | 1.62     | 2.69   | 16.11       | 0.02        | 2.82     | 8.07     |
| SEB AB (SEB)                    | 0.66     | 1.29   | 9.62        | 0.03        | 3.51     | 13.51    |
| Societe Generale (GLE)          | 0.97     | 1.19   | 6.57        | 0.03        | 1.75     | 2.44     |
| St. Galler Kantonalbank (SGKN)  | 0.07     | 0.06   | 0.28        | 0.01        | 1.52     | 1.3      |
| Standard Chartered Plc (STAN)   | 0.41     | 0.64   | 3.23        | 0.03        | 2.45     | 5.21     |
| Swedbank (SWED)                 | 0.92     | 2.4    | 22.87       | 0.03        | 4.49     | 23.1     |
| Unicredit (UCG)                 | 1.11     | 1.43   | 8.36        | 0.02        | 1.63     | 1.96     |

Table 17 Summary of Default Probabilities by country

| Country | Mean (%) | SD (%) | Maximum (%) | Minimum (%) | Skewness | Kurtosis |
|---------|----------|--------|-------------|-------------|----------|----------|
| Italy   | 1.06     | 1.12   | 5.71        | 0.03        | 1.48     | 2.06     |
| UK      | 0.91     | 1.37   | 9.82        | 0.03        | 2.89     | 9.56     |
| Spain   | 0.47     | 0.48   | 2.58        | 0.01        | 1.41     | 1.55     |
| Switzerland | 0.22 | 0.22 | 1.18 | 0.03 | 1.81 | 3.21 |
| France  | 0.88     | 1.08   | 5.4         | 0.03        | 1.78     | 2.37     |
| Germany | 1.51     | 2.21   | 15.95       | 0.07        | 3.1      | 11.56    |
| Denmark | 0.78     | 1.71   | 16.21       | 0.01        | 4.47     | 24.12    |
| Norway  | 0.54     | 1.13   | 9.11        | 0.03        | 3.93     | 15.93    |
| Austria | 0.93     | 1.39   | 9.4         | 0.06        | 2.73     | 8.07     |
| Belgium | 1.17     | 2.09   | 14.73       | 0.02        | 2.81     | 8.27     |
| Sweden  | 0.58     | 1.28   | 11.07       | 0.03        | 4.1      | 18.95    |
| Netherlands | 1.12 | 2.15 | 21.55 | 0.04 | 3.99 | 20.3 |

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