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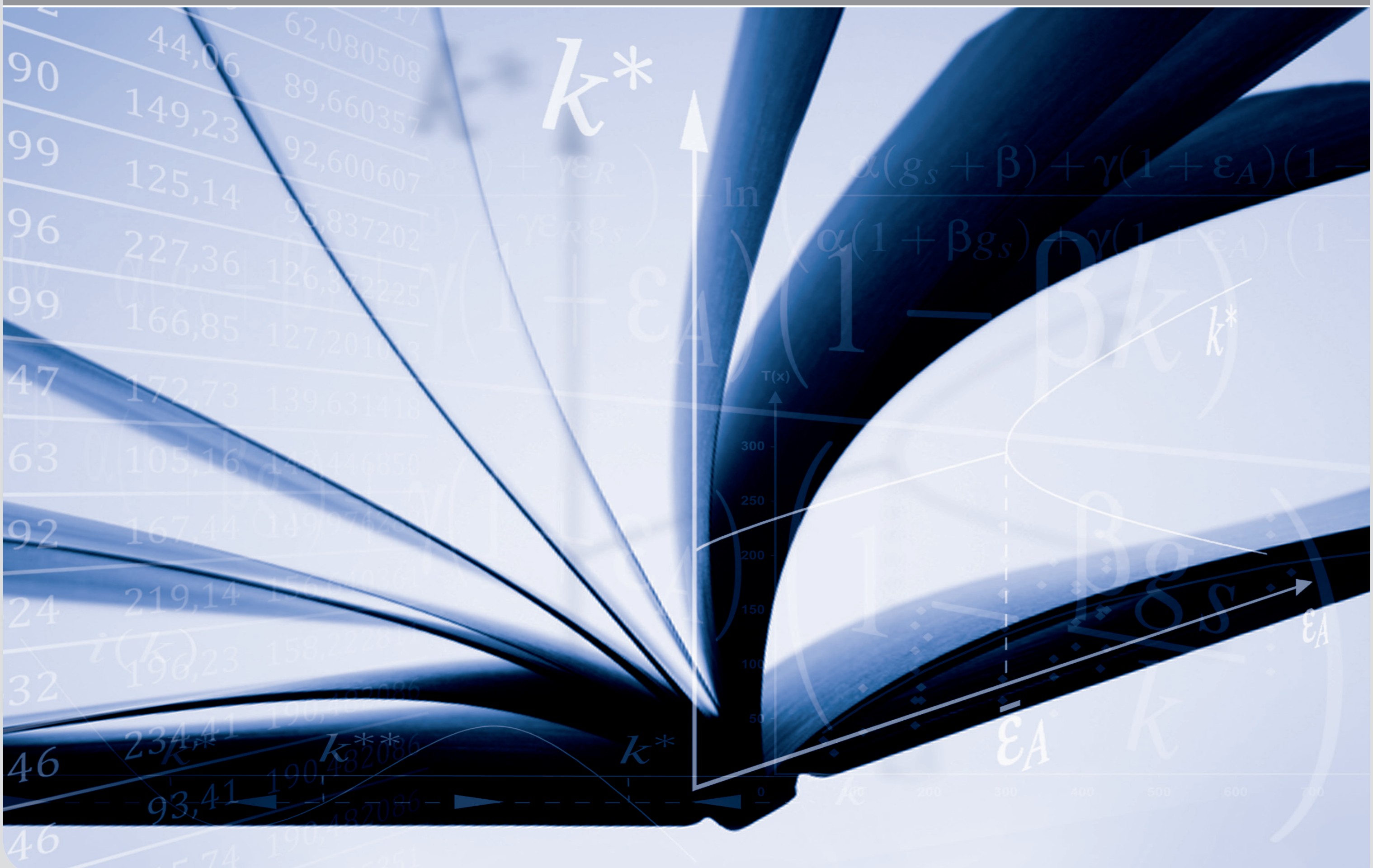

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Systemic Risk Spillovers in the European Banking and Sovereign Network *

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Abstract

We propose a framework for estimating time-varying systemic risk contributions that is applicable to a high-dimensional and interconnected financial system. Tail risk dependencies and systemic risk contributions are estimated using a penalized two-stage

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fixed-effects quantile approach, which explicitly links time-varying interconnectedness to systemic risk contributions. For the purposes of surveillance and regulation of financial systems, network dependencies in extreme risks are more relevant than simple (mean) correlations. Thus, the framework provides a tool for supervisors, reflecting the market's view of tail dependences and systemic risk contributions. The model is applied to a system of 51 large European banks and 17 sovereigns during the period from 2006 through 2013, utilizing both equity and CDS prices. We provide new evidence on how banking sector fragmentation and sovereign-bank linkages evolved over the European sovereign debt crisis, and how they are reflected in estimated network statistics and systemic risk measures. Finally, our evidence provides an indication that the fragmentation of the European financial system has peaked.

Keywords: systemic risk contribution; tail dependence; network topology; sovereign-bank linkages; Value-at-Risk

JEL classification: G01, G18, G32, G38, C21, C51, C63

1 Introduction

A lesson from the global financial crisis has been the propensity for company-specific risk to spill over to other firms. These spill-overs arise from contractual linkages in conjunction with heightened counterparty risk, but also from price effects generated, for instance, by fire sales. The result of these externalities and spill-overs has been the freezing of interbank markets observed at the height of the global financial crisis in October 2008. The market freeze was followed by a much longer period of interbank market fragmentation during the European sovereign debt crisis, with banks in core European countries no longer willing to finance banks in the periphery.

Another key feature, particularly salient during the European sovereign debt crisis, has been the interplay between fiscally strained sovereigns and stressed banks. An impaired banking sector has a limited ability to support economic activity, which in turn further strains public finances, eventually putting in question the ability of the sovereign to support the banking system in case of a need. The ECB (2011, 2014) has continuously identified this adverse feedback loop as one of the key risks to financial stability in the euro area. A better ability to understand and monitor the fragmentation of European financial markets as well as the interdependence between banks and sovereigns is thus of utmost importance for central banks and policy makers.

Quantifying these relationships empirically is challenging due to (i) the high dimensionality of the underlying financial and sovereign system, (ii) lack of public data on cross-linkages and detailed individual characteristics for a large cross-section of financial institutions and sovereigns, and (iii) the time-variability of network connections and systemic risk contributions. Moreover, for purposes of surveillance and regulation of financial systems, network dependencies in extreme risks are more relevant than simple (mean) correlations. This requires focusing on connections between (time-varying) tails, as, e.g., represented by conditional quantiles, expected shortfall or related tail measures of the underlying risk distributions. Finally, the empirical methodology should ideally produce measures and estimates that are empirically tractable and easily interpretable.

In this paper, we address these challenges and contribute to the literature both methodologically and empirically. In terms of methodology, we propose an econometric framework that allows for complex tail risk networks while producing sufficiently precise and robust estimates given the available data over relatively short (but rolling) time spans. Empirically, we provide new insights into the time-varying tail risk dependencies and spillovers between European banks and sovereigns, especially during the 2008 global financial crisis and the subsequent European sovereign debt crisis. We show how network interconnectedness, fragmentation and interactions between European financial institutions and sovereigns changed over this time period and how the state of the financial system is reflected in the topology of the underlying network.

Our methodology builds on the framework proposed by Hautsch, Schaumburg, and Schienle (2015) (henceforth HSS2015) and Hautsch, Schaumburg, and Schienle (2014). The underlying idea is to quantify the systemic impact of an individual company by the marginal effect of a firm's time-varying Value at Risk (VaR) on the VaR of the entire system. To statistically identify the relevant tail risk drivers of a specific company out of a high-dimensional set of potential characteristics (including the tail risk of other companies), HSS2015 propose using a statistical regularization and shrinkage method. The selection of individual-specific tail risk drivers gives rise to a risk network, determining to what extent the VaR of a company is driven by the tail risk of other companies. This information is then explicitly utilized in a second step, where the marginal systemic relevance of an individual firm is quantified using a quantile regression of the system VaR on the VaR of the respective company while controlling for the firm-specific risk drivers and additional economic state variables.

The explicit quantification and utilization of network dependencies distinguishes HSS2015 from alternative methods for measuring and predicting systemic risk. Adrian and Brunnermeier (2011) propose the concept of CoVaR, corresponding to a company's conditional VaR, given that the return of some other company reaches a certain benchmark value (e.g., its individual VaR). As discussed in HSS2015, there is a major conceptual difference to our methodology. The CoVaR does *not* measure the direct *marginal* effect of an individual VaR on the VaR of the system, but rather corresponds to the system VaR conditionally on the return of the particular company *realizing* its (pre-estimated) VaR. Moreover, the CoVaR does not capture any network spillovers and can only vary over time through the effects of individual VaRs. Another complementary approach to quantify systemic risk builds on Acharya, Pedersen, Philippon, and Richardson (2010). Here, systemic risk is defined as the propensity of a financial institution being undercapitalized when the financial system is under stress. This idea is put forward by Brownlees and Engle (2012) by proposing an econometric approach to measure the so-called marginal expected shortfall (MES), mainly building on time series (GARCH) methodology for asset returns. In the same spirit, Engle, Jondeau, and Rockinger (2015) measure systemic risk by the expected capital shortfall of a financial institution in a financial crisis and quantify it for a wide range of non-U.S. equities. These approaches ultimately build on the conditional asset return distribution of an individual company given distress of the market and aim at determining the capital surcharges of systemically important banks. Löffler and Raupach (2013), however, argue that pure market-based measures' ability to identify systemically important banks is limited. On the one hand, this is due the fact that extreme risks are not easily assessed based on return data. On the other hand, concepts like the CoVaR or the MES ignore tail risk dependencies induced by the underlying financial network structure. An important advantage of our approach is to explicitly take these dependencies into account when constructing the measures for systemic risk contributions. This information provides valuable additional insights into underlying tail risk connections and risk channels as perceived by the market.

In this paper, we extend the methodology introduced by HSS2015 in two directions. First, we adapt the approach to make it feasible in situations, where the density of the network is high and the underlying sample period is comparably short. In such a situation, individual companies may face tail risk spillovers from many others, making it necessary to account for large sets of individual-specific tail risk drivers when estimating companies' marginal systemic risk contribution in a quantile regression of the system VaR. The requirement to control for a large number of different risk factors, while having a comparably short estimation window, makes standard estimates inherently inefficient and unstable and - in the extreme case – even infeasible. Therefore, we propose an adaptive version of the standard shrinkage technique for determining the relevant risk drivers not only among other banks but also among sovereigns. The use of relatively short estimation windows is driven by the need to account for time-variations in companies' systemic riskiness and underlying network connections. Accounting for time variations via rolling window estimates, however, is crucial when the framework is used to surveil and monitor the system building the basis for macro-prudential regulation.

To address the trade-off between estimation robustness and the ability to capture the time-variability of the underlying relationships, we propose to combine the two-step quantile framework with a panel fixed effects approach. While controlling for company-specific fixed effects, we keep the model sufficiently parsimonious by imposing group-wise common parameters. In contrast to HSS2015, this reduces the dimensionality of the estimation problem and allows us to estimate the individual companies' marginal effect on the system VaR in one step. We show that this approach is empirically tractable and balances model flexibility and estimation robustness in the given context where the financial network is of high dimension and dense. Second, when estimating a company's systemic relevance, we explicitly account for the interconnectedness of an institution, measured by its network centrality. In particular, we allow an institution's marginal systemic relevance to be time-varying and depending – among other things – on its interconnectedness. We empirically show that the latter is a significant factor of the firm's systemic risk contribution.

Empirically, we contribute to the literature in two major directions. First, focusing on 51 large European banks allows us to cover a substantial fraction of the European banking system. Moreover, by analyzing data up to 2013, we are able to study the effects of the global financial crisis, its aftermath and the transition into the European sovereign debt crisis on the fragmentation and integration of the European financial system. Second, bringing together both banks and sovereigns in a network estimated based on CDS returns yields novel insights on the interplay between banks and sovereigns. We quantify and visualize time-varying tail dependencies, spillover directions and the density of networks, and show how banking sector fragmentation and sovereign-bank linkages evolved over the European sovereign debt crisis.

Beyond the growing literature on estimation of systemic risk contributions, our paper is also related to the papers investigating the sovereign bank-interlinkages, such as Ejsing and Lemke (2011), Alter and Schüler (2012), Arnold (2012), Bruyckere, Gerhardt, Schepens, and Vennet (2013), Alter and Beyer (2014), and Correa, Lee, Sapriza, and Suarez (2014). The key difference to the aforementioned papers, which mainly analyze contagion or spillover effects between sovereign and bank CDS spreads or credit rating downgrades, is the ability of our approach to incorporate both sovereigns and banks into tail risk networks and to track how their interconnectedness evolves over time.

Furthermore, methodologically our paper is related to earlier studies analysing contagion and co-movement in banks' equity prices, in particular to Gropp and Vesala (2009), who analyse cross-border contagion among European banks in 1994-2003 and to Bae and Stulz (2003) and Hartmann and Vries (2004), who focus on cross-country spillovers. Finally, our paper is closely related to the increasing literature analysing financial networks, contagion and systemic risk, see, e.g., Allen and Gale (2000) and Cont and Santos (2013)[1]. A major difficulty in this literature is to identify connections between banks. Unfortunately, for a wide range of banks, detailed balance sheet information reflecting counterparty risk is rarely available. Thus researchers are forced to look for suitable proxies which are widely available and sufficiently reflect network dependencies. For instance, Minoiu, Kang, Subrahmanian, and Berea (2013) quantify the connectivity between banks based on BIS bilateral locational statistics representing stocks of cross-border assets held by banking systems. Alter, Craig, and Raupach (2015) utilize a dataset of credit exposures of the German banking system. They study the effect of capital rules combining individual bank characteristics and interconnectivity measures and show the usefulness of capital rules based on eigenvectors of the adjacency matrix.

The key findings of our paper are as follows: We first document how the topology of our tail-dependence networks evolves over time. In particular, we observe that the density of the tail dependence network based on equity prices increases from 2006 onwards, peaks around the height of the global financial crisis and significantly declines thereafter. We further show that during the European sovereign debt crisis in 2011-2013 financial markets fragment along national borders. This is reflected by a strong increase of domestic (within-country) linkages. This increase is more pronounced for economies engulfed by the sovereign debt crisis. Third, the CDS price networks show that financial market fragmentation during the sovereign credit crisis is accompanied by increased interconnectedness between sovereigns and banks. Again, this increase is more pronounced in economies at the center of the sovereign debt crisis.

[1] See Chinazzi and Fagiolo (2013) for a recent review of this literature.

We then present banks' contribution to systemic risk at the height of the sovereign debt crisis. Unsurprisingly, banks from EU-IMF programme countries exhibit on average high contributions to systemic risk. We also document that marginal systemic relevance increases with size, leverage, and interconnectedness. The systemic risk ranking at the height of the sovereign debt crisis differs markedly from the one obtained during the peak of the global financial crisis when large, international banking groups dominate the ranking.

From a methodological point of view, we show the importance of explicitly linking an entity's interconnectedness to its (time-varying) systemic risk contribution. This information provides valuable additional insights into underlying tail risk connections and risk channels as perceived by the market, and is an important advantage of our approach compared to concepts like the CoVaR or MES, which do not explicitly take into account interconnectedness. Additionally, our proposed method, the combination of the two-stage panel framework with a panel fixed effects approach, turns out to provide sufficiently robust estimates given data availability and the necessity to address a dense tail risk network.

The remainder of the paper is organized as follows. Section 2 explains the estimation methodology while Section 3 describes the dataset. Section 4 presents the results and is divided into three subsections: Subsection 4.1 illustrates the estimated time-varying tail risk networks, Subsection 4.2 describes the sovereign-bank interactions, while Subsection 4.3 presents the systemic risk contributions. Finally, Section 5 concludes.

2 Methodology

Our empirical methodology for estimating systemic risk contributions is based on two steps. The first step is necessary for determining the time-varying topology of the underlying tail risk network of banks and sovereigns. While the risk network contains valuable economic information on its own, it is indispensable for identifying the systemic risk contribution of a bank in a densely interconnected system. The outcome of this step is the estimated conditional VaR of each institution given the underlying network structure and economic state variables. The second step explicitly utilizes information on the identified network to estimate an individual institution's marginal impact on the system VaR.

2.1 Time-Varying Bank-Sovereign Networks

We construct generalized tail risk networks for the European bank-sovereign system by adapting and extending the approach in Hautsch, Schaumburg, and Schienle (2015). In particular, we account for potentially time-varying bank-sovereign spillovers and explicitly include sovereigns as important parts of the generalized European financial network. The main idea is to empirically determine a network link from bank/sovereign j to bank/sovereign i, whenever the tail risk of i is (positively) affected by the distress of j. Denoting the equity or CDS return of bank/sovereign i by X_t^i, the tail risk of i is reflected by its conditional Value-at-Risk (VaR), $VaR^i_{q,t}$, given a set of i-specific risk drivers R^i_t, i.e.,

$$\Pr(-X^i_t \geq VaR^i_{q,t}|R^i_t) = q, \tag{1}$$

with $VaR^i_{q,t}$ denoting the (negative) conditional q-quantile of X^i_t.[2] The distress of a bank/sovereign is identified by the corresponding return being below its empirical 10% quantile. Accordingly, we define a so-called loss exceedance by $N_{t,j} = X^j_t \mathbf{1}(X^j_t \leq \hat{Q}^j_{0.1})$, where $\hat{Q}_{0.1}$ is the unconditional 10% sample quantile of X^j_t.

The entire set of tail risk drivers of a bank/sovereign i thus consists of loss exceedances of banks/sovereigns other than i, captured by a vector N^i_t with elements $N_{t,j}$ for $j \neq i$, and additional observable control variables Z^i_t. These externalities Z^i_t contain lagged macro-financial state variables, and, in case of banks, i-specific balance sheet characteristics. Specifying VaR^i_t as a linear function of the regressors yields

$$VaR^i_t = \alpha^i_0 + \alpha^i_1 Z^i_t + \alpha^i_2 N^i_t. \tag{2}$$

In theory, it appears straightforward to estimate this model by standard linear quantile regression techniques (see Koenker and Bassett (1978)) accounting for time variation in the structural relation by rolling windows. In practice, however, this is infeasible as the number of loss exceedances N^i_t potentially affecting i is large. Including the entire set N^i_t as regressors in the model would result in highly imprecise and unstable estimates. Moreover, (sequential) tests on the statistical significance of individual variables are virtually infeasible with outcomes hardly interpretable.

Following HSS2015, we therefore statistically identify the subset of *relevant* i-specific loss exceedances, denoted by $N^{(i)}_t$, from the full set of potential network influences N^i_t by a model shrinkage technique. In particular, we use a weighted version of the least absolute shrinkage and selection operator (LASSO) approach for quantile regression as introduced by Belloni and Chernozhukov (2011). The idea is to run a penalized quantile regression to find the estimate $\hat{\alpha}^i$ of $\alpha^i := (\alpha^i_0, \alpha^i_1, \alpha^i_2)$ by

$$\widetilde{\alpha}^i = \text{argmin}_{\alpha^i} \frac{1}{\tau} \sum_{t=1}^{\tau} \rho_q \left(X^i_t + \alpha^i_0 + \alpha^i_1 \tilde{Z}^i_t + {\alpha_2}^i \tilde{N}^i_t \right) + \lambda^i \frac{\sqrt{q(1-q)}}{\tau} \sum_{k=1}^{K} w^i_k \hat{\sigma}_k |\alpha^i_{2,k}| \ , \tag{3}$$

where τ denotes the number of observations, $\tilde{Z}^i_t$ and $\tilde{N}^i_t$ denote the set of *potential* (demeaned) regressors Z^i_t and N^i_t, $\rho_q(u)$ is the quantile loss function $\rho_q(u) = u(q - I(u < 0))$ at level q with the indicator $I(\cdot)$ being one for $u < 0$ and zero otherwise, and $\hat{\sigma}_k$ is the empirical standard deviation of the k-th component in N^i_t.

The coefficient λ^i is a penalty parameter, which penalizes regressors which do not sufficiently contribute to the objective function, and thus are not relevant for the model. Due to the penalization, the coefficients of these regressors are shrinked towards zero. Hence, the penalization component allows us to identify *relevant* loss exceedances as those regressors with sufficiently large marginal effects. Correspondingly, a regressor

[2] We use the convention that VaR_q is defined as the negative conditional q-quantile such that higher levels of risk are reflected by higher levels of VaR.

is de-selected if its (adaptive) LASSO estimate in $\widetilde{\alpha}_2^i$ is close to zero. The strength of the penalization is therefore governed by λ^i with the number of eliminated regressors increasing in λ^i. For instance, for $\lambda^i = 0$, we obtain the standard quantile regression problem according to Koenker and Bassett (1978). As loss exceedances of banks and sovereigns might be of quite different magnitudes, it is important to allow for regressor-specific penalizations w_k^i. Both λ^i and w_k^i are chosen in a data-driven way by optimizing based on the score of (3) with remaining constants and thus maximizing the in-sample predictive ability of the resulting post-LASSO quantile specification. The quality of the in-sample fit is evaluated based on the model's backtesting performance. The details of this procedure are presented in the Appendix. Finally, retaining only the regressors, which are not de-selected by the weighted LASSO results into the corresponding 'post-LASSO' VaR specification.

The weighted quantile LASSO approach is performed for each bank and sovereign i. The final set of post-LASSO regressors yields the set of i-specific tail risk drivers. Then, the weighted LASSO-*selected* i-specific loss exceedances $N_t^{(i)}$ constitute directed network impacts to bank i. By moving through all banks in the system, we thus obtain a network graph showing tail dependence relationships among banks conditional on the control variables Z_t^i.

In contrast to HSS2015, we allow for time-variations in network dependencies and perform the analysis based on rolling windows, where sample windows of 24 months are rolled over at a yearly frequency.[3] In particular, at the beginning of each period, indexed by t_0, we determine relevant risk drivers based on the weighted LASSO approach utilizing information from the previous two years. Networks are thus year-specific and can vary on an annual basis. Correspondingly, the VaR of firm/sovereign i at day t in year t_0 is determined as

$$\widehat{VaR}_t^{i,t_0} = \widehat{\alpha}_0^{i,t_0} + \widehat{\alpha}_1^{i,t_0} Z_t^i + \widehat{\alpha}_2^{i,t_0} N_t^{(i,t_0)}, \tag{4}$$

where $N_t^{(i,t_0)}$ is the set of i-specific loss exceedances selected by the LASSO procedure for the period indexed by year t_0 and the coefficients $\widehat{\alpha}_0^{i,t_0}$, $\widehat{\alpha}_1^{i,t_0}$ and $\widehat{\alpha}_2^{i,t_0}$ are obtained by the year-t_0 post-LASSO quantile regression.

This approach is performed in Section 4 to estimate (i) tail risk networks of financial companies based on equity returns with sovereigns' bond returns serving as (non-penalized) state variables and (ii) joint tail risk networks of both banks and sovereigns based on corresponding CDS returns. For all networks, we use a $q = 5\%$ VaR. For more details on the choices of Z_t^i and N_t^i, see Section 4.

2.2 Evaluating Systemic Impact

We define the systemic risk contribution of a bank as the total realized impact of a change in a bank's VaR on the VaR of the entire system. Following HSS2015, we denote this

[3]With an estimation window of 24 months, a sufficient amount of observations occur in the extreme 5 and 10% quantiles such that point estimates have an acceptable precision and are still based on the most recent information only. In order to limit computational complexity but to gain an overall picture of the time evolution of the network, we use yearly rolling windows.

effect as realized systemic risk beta. To quantify this measure, the system VaR, denoted by VaR_t^s, is defined as the VaR of a value-weighted portfolio of firms representing the financial system. Moreover, as explained in more detail below, we build groups $g = 1, \dots, G$ of institutions, which allows us to estimate *group-specific* marginal effects of certain variables instead of individual-specific marginal effects.

Thus, the effect of the estimated $\widehat{VaR}_t^{i,t_0}$ on VaR_t^s in a dense network within a given group g of banks at time point t in year t_0 is obtained from

$$VaR_t^s = \beta_g^{t_0}(B_t^i, net_t^{i,t_0})\widehat{VaR}_t^{i,t_0} + \gamma^{i,t_0} + \theta_1^{t_0} Z_t^s + \theta_2^{t_0} R_t^{(i,t_0)} , \tag{5}$$

where B_t^i denote firm-specific characteristics, and net_t^{i,t_0} denotes an i-specific local network measure, defined as the logarithm of one plus the out-degree of node i in the network topology. Furthermore, γ^{i,t_0} is a firm-specific fixed effect, $R^{(i,t_0)}$ is a value-weighted index of the VaRs of all banks selected as being relevant for bank i in the first step, and Z^s contains lagged macro-financial state variables.

The parameter $\beta_g^{t_0}$ is the (time-varying) marginal effect and is referred to as *systemic risk beta* for group g. The specification implied by (5) constitutes a major difference to HSS2015. In HSS2015, the system VaR is linked to the VaR of each individual institution while controlling for its specific tail risk drivers. This results in a set of equations for VaR_t^s with i-specific regressors. In a high-dimensional and dense network, however, this yields a high-dimensional system of highly parameterized specifications which becomes practically infeasible and numerically instable if the sample size is not sufficiently high. To overcome this problem and to make the approach feasible in high dimensions, we therefore suggest to restrict several parameters to be common and group-specific and estimate VaR_t^s in one step.

Apart from time variations of $\beta_g^{t_0}$ arising from the rolling window estimation, we allow for additional variation *within* a two-year period (indexed by t_0) by modeling $\beta_g^{t_0}$ as a function of firm-specific characteristics B_t^i and the i-specific network measure, net_t^{i,t_0}. The latter characterizes the firm's interconnectedness in the corresponding year-t_0 network topology at time t, and thus explicitly links a firm's marginal systemic relevance to its role in the underlying tail risk network.[4] This specification extends the initial setting by HSS2015 to explicitly allow for feedback effects between a firm's interconnectedness and its VaR's marginal effect on the system VaR. To keep the approach computationally tractable, we assume $\beta_g^{t_0}$ being linear in its components within a group $g \in \{1, \dots, G\}$ of similar institutions in a dense network, i.e.,

$$\beta_g^{t_0}(B_t^i, net_t^{i,t_0}) = \delta_{0,g}^{t_0} + \delta_{1,g}^{t_0} B_t^i + \delta_{2,g}^{t_0} net_t^{i,t_0}. \tag{6}$$

The grouping of institutions is necessary in order to balance robustness of the obtained beta measure against the variability required for consistent estimation of the effect. Hence, pooling together firms which are similar in terms of their (average) marginal systemic impact and their marginal effects with respect to the variables B_t^i, allows group-wise estimation of the parameters in (6) instead of individual-wise. In contrast, working with

[4]The specification $net^i = \log(1+\text{out-degree}^i)$ exploits the directed nature of the network. Conditioning on the risk driver index $R^{(i,t_0)}$ controls for *incoming* linkages.

only one large panel without subgroups for all institutions would induce too much rigidity on the common parameters. The inclusion of the individual-specific fixed effect, γ^{i,t_0}, and the aggregated indicator for network spillover influences on beta, $R^{(i,t_0)}$, allow to control for i-specific effects and provide a robust way to obtain unbiased estimates of $\beta_g^{t_0}$. In practice, we suggest a simple and straightforward data-driven procedure to obtain adequate groups, which we outline below in the empirical section. Thus, the choice of grouping is objective and yields a stabilizing effect on the obtained systemic risk beta in a dense network.

The full specification is then estimated by a single (pooled) quantile SUR system regression with the inclusion of appropriate group and bank specific dummies. The system is obtained analogously to a system formulation of a set of linear equations. The latter are given by (5) for each company i. The system then gives rise to a vector containing (repeated) equation-specific realizations of VaR_t^s, a block-diagonal regressor matrix collecting equation-specific regressors in each block, and a stacked vector of parameters. The latter, however, is restricted as the coefficients of control variables from the system Z^s and from the network $R^{(i,t_0)}$ are common across all institutions, and influences of balance sheet characteristics on $\beta_g^{t_0}()$ only vary across subgroups in estimates of $\delta_{1,g}^{t_0}$. Likewise Z^s is common across all equations. Note that despite group-specific common parameters in (6), an individual bank's systemic risk beta $\beta_g^{t_0}()$ still varies on an individual basis as it depends on i-specific variables B_t^i and net_t^{i,t_0}. Moreover, γ^{i,t_0} differs across all banks and captures individual fixed effects. This model and estimation strategy yields stabilized parameter estimates by exploiting as much cross-sectional variation as possible without losing consistency of the estimate for $\beta_g^{t_0}$. Moreover, we can estimate all coefficients of (5) and (6) in one step, in contrast to a multiple-equation estimation as in HSS2015. Finally, the included fixed effects γ^{i,t_0} capture potentially neglected bank-specific covariates making the approach more robust to potential misspecification.

Finally, we obtain an estimate of the *realized* systemic risk beta $\beta^{s|i}$ as

$$\widehat{\beta}_t^{s|i} := \hat{\beta}_g^{t_0}(B_t^i, net_t^{i,t_0})\widehat{VaR}_t^{i,t_0}. \tag{7}$$

Based on this measure we assess the overall systemic importance of institutions. It reflects the total realized effect of an increase in a bank i risk level on the risk of the entire system. This impact consists of the direct impact via the idiosyncratic VaR but also of a potential change in the marginal systemic effect via $\beta_t^{s|i}$. Our rankings in the following are based on *realized* systemic risk betas in the $5\% - VaR^s$.

3 Data

Our dataset consists of 51 large European banks, which we choose based on the following criteria. First, we select the largest European banks, covering up to 90% of the European banking system's total assets (in 2010), which results in 74 banks. Second, as the empirical analysis requires equity price data, we keep only the publicly traded and listed banks in the sample, which leaves us with 53 listed banks, covering 72.4% of the European banking system's total assets. Third, two further banks (Bankia and Österreichische

Volksbanken) are dropped from the sample due to data limitations. The list of the 51 banks in the sample is shown in Table 1. The financial system in the second stage is represented by the Stoxx Europe 600 Financial Services index, where we use daily observations. For each institution, we use daily equity price returns and as bank specific risk drivers quarterly balance sheet data covering the period from 01/07/2006 to 30/06/2013. For the CDS networks, we employ available daily changes (first differences) in 5-year senior CDS spreads.

As VaR^i-specific control variables Z_t^i, we choose a set of *bank-specific* balance sheet characteristics. These include leverage, measured as total assets over total equity, to capture the fragility of a bank. Furthermore, we also use loan loss reserves and return on assets, which represents asset quality. Additionally whereas the cost-to-income ratio and the price-to-book ratio measure management quality. The return on equity measures a bank's capacity to generate earnings, while the ratio of net short-term borrowing to total liabilities and the loan-to-deposit ratio capture liquidity risk. The size, measured as total assets, proxies for the bank being too big to fail. As all balance sheet data is available only quarterly whereas stock or CDS prices are daily, each piece of balance sheet information enters the regression at its release date to obtain results in real-time.

The dataset also includes macro-financial state variables which are all observed daily. We use the Euribor-OIS spread as a barometer of distress in money markets covering both liquidity and credit risk. The VDAX index measures implied volatility in the German stock market, proxying for investors' risk appetite. The macro-financial state variables listed above are also used as control variables Z_t^s in the second stage regression. Moreover, B_t^i contains the subset of balance sheet characteristics with a distinct macroprudential interpretation, in this case leverage and size as defined above.

To represent sovereign risk, we also collect data on the sovereigns of the countries where the banks are headquartered. Thus, our sample includes the following sovereigns: Austria, Belgium, Cyprus, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Sweden and the UK. The data include the daily yields on 10-year benchmarks bonds, the slope of the yield curve as measured by the daily yield difference between 10-year and 2-year bonds as well as the daily changes (first differences) of 5-year sovereign CDS spreads[5].

Tables 1 and 2 provide basic summary statistics of the stock and CDS returns of the banks and sovereigns in the sample. All financial variables employed in the analysis as well as the regressors mentioned above are tested to be stationary. The data source for all economic and financial variables is Bloomberg.

[5]Greece could not be included in the CDS network analysis as there was no trades of Greek CDS following the sovereign debt restructuring in March 2012 until May 2013.

4 Results

4.1 Time-varying tail risk networks of banks

Figures 1 and 2 and Tables 3 and 4 visually and quantitatively characterize the evolution of tail dependence networks of all financial companies over all six (overlapping) two-year sub-periods. Here, the control variables Z_t^i in (2) contain company-specific characteristics and macroeconomic state variables as described in Section 3. We measure a bank's interconnectedness by its network degree and graphically illustrate it by the size of the nodes in Figures 1 and 2. In the figures, we label all banks whose degree is above the 75th percentile of the degree distribution in the respective subperiod. The shape of each network is obtained by minimizing the length of all aggregated network connections between all institutions. Correspondingly, the most connected firms are located in the center of the network graph.

The main findings can be summarised as follows. First, the density of the network increases between 2006 and 2008, peaks in the 2008-2010 period and declines thereafter. At the height of the global financial crisis (2008/09), we observe the strongest estimated interconnectedness between European banks, as reflected by the size of the nodes and the number of identified linkages. The network structure in the subsequent periods (from 2010 onwards), however, indicates a clearly different picture. Here, the interconnectedness between the banks strongly declines and the European banking system becomes more fragmented. This is most obvious in the period 2010-2012, reflecting the height of the European sovereign debt crisis.

According to Figures 1 and 2, the density of the network clearly varies over time indicating that the financial system is moving through different states. This is confirmed by the corresponding network densities reported in Table 3.[6] The network density increases from 0.07 in the first subperiod to 0.08 at the height of the global financial crisis. In contrast, during the European sovereign debt crisis, the network density decreases to 0.04. The pattern is intuitive as one would expect tail dependence between banks to increase during a financial crisis. Conversely, a stronger role of sovereigns in transmitting shocks should be reflected in sparser tail dependencies between banks. Since sovereign bond returns serve as non-penalized control variables, a stronger impact thereof might be responsible for the decline of network density after 2008. Tail dependence networks where sovereigns are not used as control variables but as risk drivers (see Section 4.2) confirm the view that the decline of network densities in bank-only networks during the period 2010 to 2013 reflects mainly the increasing role of sovereigns. On the other hand, the increase in network densities from 0.04 to 0.05 between the two last subperiods suggests that the intensity of the sovereign debt crisis has to some extent receded.

The colour of the nodes, indicating the countries where the banks are headquartered, illustrates the impact of country-specific developments on the network structure. While during the 2006-2008 period, the most interconnected firms originate pre-dominantly

[6] The network density is calculated as the number of actually observed connections in the network divided by the number of possible connections for the given nodes.

from Spain, but also from France, Portugal and Ireland, in the subsequent period also Italian and British banks move to the center of the network. Both network graphs depict pronounced country-specific clusters with strong cross-country links, in particular, among banks in the center of the network. These developments might already indicate upcoming problems in the banking sector of these countries, partly driving the European sovereign debt crisis in 2012/13. While these 'national clusters' disappear in the height of the global financial crisis (reflected by the 2008-2010 subgraph), they become very pronounced in the aftermath.

The sovereign debt crisis in particular is characterized by a strong fragmentation of the financial network with 'domestic' linkages (i.e., linkages between companies within a country) becoming increasingly prominent. This is confirmed by Table 3, showing that the share of domestic linkages (relative to all linkages) has increased from 0.28 in the 2008-2010 sub-period to 0.52 in the 2010-2012 sub-period. Again, the slight decrease to 0.45 in the latest sub-period might reflect a relaxation of the sovereign debt crisis. This is most obvious for financial institutions in Greece and Cyprus, Italy, Spain and Portugal, and (partly) France. Particularly Greece and Cyprus move towards the fringe of the network. In the 2010-2013 sub-periods, they are totally disconnected from the rest of the network. Also Spanish and Portuguese banks jointly leave the center of the network (2009-2011), with in particular the Portuguese banks becoming increasingly disconnected from the rest of the system.

Table 4 provides the shares of domestic links separately for countries, which have been particularly affected by the sovereign debt crisis (in particular, Cyprus, Greece, Ireland, Italy, Portugal, and Spain) and all other countries. It turns out that countries affected by the sovereign debt crisis display on average a higher share of domestic linkages. This is most pronounced during the 2009-2011 and the 2010-2012 period, and is consistent with the notion that financial fragmentation has primarily affected banking systems in the European periphery.

During the financial crisis periods (Figure 1), we observe that some banks are particularly strongly interconnected. In the 2006-2008 sub-period, the Spanish banks Banco Santander, Banco de Sabadell and Banco Popular Espanol are in the center of the tail dependence network. The French banks BNP Paribas, Credit Agricole and Societe Generale, as well as the Portuguese Espirito Santo Financial Group, the Belgian Dexia, the Irish Bank of Ireland, the British Royal Bank of Scotland and the German Commerzbank stand out as strongly interconnected banks. In the 2007-2009 sub-period, the Spanish banks Banco de Sabadell and Banco Popular Espanol are most strongly interconnected, while in 2008-2010 this role is taken by the Italian Banco BPI. Banco de Sabadell and the Royal Bank of Scotland constantly appear among the most interconnected banks in the first three of the six subperiods. Finally, Credit Agricole is also highly interconnected in the first sub-period and at the height of the financial crisis.

4.2 Sovereign-bank interaction

Complementing the analysis above by a corresponding analysis based on CDS data opens up a valuable additional perspective. CDS prices reflect investors' expectations on default risks, and thus are explicitly connected to extreme market movements. Moreover, utilizing CDS returns allows us to construct and analyze a network containing *both* financial companies and the underlying sovereigns. This complements the analysis above, where information on sovereign risk enters the analysis only via respective bond returns used as economic state variables. According to the ECB and the IMF[7], the European sovereign debt crisis is characterised by the interplay of fiscally constrained sovereigns and weak banking systems. Exploiting CDS prices enables us to study to what extent this relationship is also reflected in the tail dependence networks.

The network construction differs from the procedure explained in Section 4.1 in the following way: First, instead of using equity returns as the underlying variable we utilize CDS returns of banks *and* sovereigns. Accordingly, bank and sovereign CDS returns are both penalized in the weighted LASSO approach. As illustrated below, we will have a lower level of penalization, which is reflected in higher network densities. Second, when modeling the VaR of a bank, Z_t^i consists of bank-specific balance sheet characteristics and macro-financial state variables (as described in Section 3). For the VaR of a sovereign, we only include macro-financial state variables.

Figures 3 and Figure 4 present the corresponding CDS-based networks. The figures reflect the implications of the sovereign debt crisis in the sense that some sovereigns (represented by square vertices), mostly those affected by the crisis, move towards the center of the networks. This is particularly true in the aftermath of the global financial crisis and during the rise of the sovereign debt crisis (2010-2012). Particularly, the CDS tail risks of France, Italy and Spain become deeply connected with the tail risks of financial companies. Italy stands out as the most important sovereign according to this topology, but also France and Spain exhibit a high degree of interconnectedness in 2010-2012. This shape persists also in 2011-2013, with Portugal, Ireland and Austria also gaining importance. The centrality of the German sovereign, on the other hand, is comparatively low, confirming Germany's role as an anchor of stability as opposed to a transmitter of tail risk.

Table 5 shows that the evolution of network density over time resembles that of the bank networks above until the period 2008-2010. In both cases, they peak during 2008-2010. The CDS-based networks, however, reach another high during 2011-2013, for which the network density is equal to the crisis peak level. This suggests that tail dependence as measured by network density in sovereign-bank networks can serve as an indicator for the intensity of the crisis. While the 2010-2012 period was just as critical to the survival of the European Monetary Union as the 2008-2010 period, the former was not detected as problematic by pure bank networks.

[7] See, e.g., ECB Financial Stability Reviews (2011, 2012) or the IMF Global Financial Stability Reviews (2011, 2012).

The increase of sovereigns' interconnectedness is particularly true for countries which have been strongly affected by the sovereign debt crisis (so-called 'crisis countries'), i.e., Ireland, Italy, Portugal and Spain. According to Table 6, the interconnectedness of 'crisis countries' and 'non-crisis countries' is relatively similar during the global financial crisis (2006-2008).[8] In the subsequent periods, however, we observe a clear increase of the average centrality of 'crisis countries', while the centrality of the other countries is affected much less. These results indicate that a simple network statistic, as the network degree, captures substantial information about the evolution of a sovereign's contribution to systemic risk.

The share of sovereign-bank linkages, as shown by Table 7 supports this view: During the global financial crisis, 'crisis countries' show, on average, a slightly lower share of sovereign-bank linkages than the others. With the advent of the European sovereign debt crisis, however, this reverts. The share of sovereign-bank linkages of 'crisis countries' increases, while that of the other countries remains at about the same level. Hence, this is not only due to the increasing interconnectedness of a sovereign, but obviously due to the increase of linkages to financial institutions. Italy displays a particularly high share of sovereign-bank linkages, whereas that of Germany is comparatively low. In contrast, the time evolution of financial fragmentation, as represented by the share of domestic linkages, resembles that of the bank networks analyzed in Section 4.1. Again, fragmentation peaks during 2010-2012 before receding slightly.

4.3 Systemic risk contributions

Building on the estimated banking network structure in Section 4.1, we estimate the systemic risk contribution of a bank based on (5) and (6). The choice of the underlying grouping follows two criteria: On the one hand, banks within a group should preferably be similar in terms of their average marginal systemic impact and in how the characteristics B influence this effect. In this case, the coefficients of components of the systemic risk beta (6) are captured sufficiently well by the corresponding *common* parameters within the group. We aim to keep the number of groups small to ensure the availability of a sufficient number of observations per group and thus the precision of the resulting estimates. Investigating different combinations and number of groups, we find that a regression based on three groups is the most appropriate. In particular, the first group contains all banks below the overall empirical median in size and below median in leverage; the second is below median in size and above median in leverage, or vice versa; and the last is above median in size and above the median in leverage.

Figure 5 shows the estimated systemic risk network at the height of the European sovereign debt crisis in June 2012. It stems from the baseline specification used in Section 4.1. While depicting the underlying network structure, we visualize the magnitude of the estimated systemic risk beta, the corresponding VaR and the resulting total effect corresponding to the product of the two and referred to as realized systemic risk. Again,

[8]The first period is discarded due to lack of data for Denmark, the Netherlands, Sweden and the UK.

the node sizes reflect the quartiles of the corresponding underlying (cross-sectional) distributions with banks being in the respective top quartile explicitly labeled.

The first two plots of Figure 5 highlight the differences between the individual and the systemic perspective. The banks that rank highly in the marginal systemic relevance distribution are comparatively large and well known entities, including BBVA and Santander from Spain, or Barclays, HSBC, and Royal Bank of Scotland from the UK. The banks that rank highly in the VaR distribution, on the other hand, are mainly from crisis countries. For instance, all banks headquartered in Greece and Cyprus are in the highest quartile of the VaR distribution. At the same time, they exhibit only moderate correlations with the left tail of the risk index. Conversely, the Swedish banks display a comparatively strong correlation with the risk index, but are safe individually.

The third plot of Figure 5 shows the distribution of realized systemic risk, thus containing the individual and the systemic perspective. Banks in the fourth quartile of the distribution tend to rank highly in one risk metric and to exhibit an intermediate level in the other metric. Only three banks which are typically considered as belonging to the core euro area are in the fourth quartile of the realized systemic risk distribution: Dexia, KBC, and Natixis. Perhaps more surprisingly, this is true for only one bank each from Italy and Spain, despite the pressure exerted by financial markets at this stage of the sovereign debt crisis. Less surprisingly, five banks from the crisis countries are present in the fourth quartile of the realized systemic risk distribution.

Table 8 presents the overall ranking of institutions based on realized systemic risk betas reporting also its multiplicative components. In Table 9, the focus is on marginal systemic relevance and the ranking is based purely on this factor in June 2012. Moreover, it provides insights into its driving parts by listing the associated group as well as the impact of bank's size, leverage and interconnectedness. The table shows that the estimated systemic risk beta increases with size and leverage as captured by our grouping. The last column demonstrates that more interconnected banks likewise display a higher degree of tail dependence. Thus, size, leverage, and interconnectedness affect the estimated systemic risk beta in line with prior expectations. More importantly, the results suggest that traditional balance sheet characteristics alone provide an incomplete account of systemic relevance.

Additionally, we show the results of our analysis for another key period, October 2008, right after the default of Lehman Brothers on 15 September 2008. Similarly to the analysis above, Figure 6 illustrates the marginal systemic relevance, the Value-at-Risk and realized systemic risk contributions of the individual European banks during the peak of the global financial crisis. Likewise, Tables 10 and 11 show the overall ranking based on the realized systemic risk as well as its components. In October 2008, we observe the highest systemic risk for Dexia, Bank of Ireland, Royal Bank of Scotland, Commerzbank and KBC. In case of Dexia, Royal Bank of Scotland and Commerzbank, this is explained by a high estimated systemic risk beta, and in particular high leverage and size. In contrast, the high estimated systemic risk contribution of Bank of Ireland and KBC is mainly explained by a high level of Value-at-Risk. The difference between the estimated systemic risk rankings in October 2008 and June 2012 is noticeable. While Dexia, Barclays, Royal Bank of Scotland as well as Irish Life and Permanent rank high in terms of their estimated systemic risk contributions in both periods, the top ranking banks clearly differ.

In the latter period, several banks from countries participating in the EU-IMF programme occupy the highest ranks, while in the former period, large, international banks such as Royal Bank of Scotland, Commerzbank, Credit Agricole, Barclays, Societe Generale and Lloyeds rank highly.

Figure 7 shows the distribution of the systemic risk beta, Value-at-Risk and realized systemic risk conditional on whether banks have received a capital injection in the fourth quarter of 2008.[9] All risk measures point in the same direction and are higher for those banks that were subject to capital injections. The realized systemic risk measure combining both the individual and systemic perspective is apparently better at discriminating between the two groups than either of the other measures. This is intuitive as many of the banks that failed at the height of the financial crisis were the large international banks.

Figure 8 presents the same comparison for the second quarter of 2012. In this period, a slightly different picture emerges. As in 2008, banks that were re-capitalized in the second quarter of 2012, exhibit a higher median Value-at-Risk and thus are considered as being fragile by market participants. The systemic risk beta, however, appears to be lower. Though this results seem to be counterintuitive at first glance, it becomes plausible when considering the identity of the banks. Actually, four of the eight banks that received a capital injection were Greek.[10] The re-capitalization followed the Private Sector Involvement in March 2012. Thus contagion links between Greek banks and the rest of the European banking system had been severed by then. This is consistent with the structure of the tail dependence network, where the separate component formed by Greek and Cypriot banks suggests that these were subject to different shocks than the rest of the European banking system.

Figure 9 shows how in the case of four sample banks, the marginal systemic relevance evolves over time. Particularly Allied Irish and Dexia exhibit a considerable time variation. The marginal systemic relevance of Allied Irish peaked before Ireland signed the economic adjustment programme with the Troika in the second half on 2010. By June 2012, it then declined to less than a quarter of its maximum. Analogously, the marginal systemic relevance of Dexia was at its all time high in the run-up to its first bailout in the fall of 2008. Moroever, the figure separates the marginal systemic relevance $\beta_g^{t_0}(B_t^i, net_t^{i,t_0})$ into its underlying components. In particular, we quantify the contribution of a bank's interconnectedness (as reflected by net_t^{i,t_0}) by $\delta_{2,g}^{t_0} net_t^{i,t_0}$, whereas that of the other components is given by $\delta_{0,g}^{t_0} + \delta_{1,g}^{t_0} B_t^i$ with B_t^i including size and leverage. The plots illustrate the fact that network effects matter. In particular, it seems that interconnectedness is comparatively more important for the below median leverage and size banks in group 1 (such as Allied Irish), and the above median and size banks in group 3 (like Barclays or Dexia) than banks in group 2 with leverage and size being in opposite categories (such as Santander).

[9] Data on capital injections come from Betz, Oprica, Peltonen, and Sarlin (2014). The following banks were recapitalized in October 2008: Credit Agricole, BNP Paribas, Commerzbank, Dexia, Erste Bank Group, Societe Generale, KBC, Royal Bank of Scotland, and Swedbank.

[10] The following banks were re-capitalized in the second quarter of 2012: Alpha Bank, Banco Comercial Portugues, Monte dei Paschi, Banco BPI, Marfin, National Bank of Greece, EFG Eurobank, Piraeus.

Figure 10 shows the relative proportions of interconnectedness as a share of marginal systemic relevance $\delta_{2,g}^{t_0} net_t^{i,t_0} / \beta_g^{t_0}(B_t^i, net_t^{i,t_0})$. The plot associated with Allied Irish suggests that up to 2011 about 70% of the bank's marginal systemic relevance was due to interconnectedness. Similarly, our estimates attribute about 40% of Dexia's marginal systemic relevance before the second bailout to interconnectedness. Both banks have a zero contribution of interconnectedness in the penultimate and the last two subperiods, respectively. This follows from an out-degree of zero in the corresponding tail dependence networks.

4.4 Robustness Checks

To validate our analysis, we conduct various robustness and sensitivity checks: First, we analyze the sensitivity of the results with respect to the choice of the risk index $R^{(i,t_0)}$. While the form of weighting (e.g., equal-weighting versus value-weighting) does not qualitatively change the results, its role as a control variable for a consistent estimation of systemic risk betas is distinct. Actually, omitting $R^{(i,t_0)}$ influences the estimates of systemic risk betas and consequently the resulting systemic risk ranking. Second, we check the dependence of beta estimates on the number of underlying groups. Using, for instance, an even rougher categorization based on two groups only, has very mild effects on the final outcomes. Hence, our estimates show sufficient stability with respect to the underlying grouping. Third, we redo the analysis by including asset growth as an additional control in the vector B. This extension, however, produces multi-collinearity effects inducing unstable estimates. Therefore, a specification with leverage, size and net_t^i as the drivers of time variation in systemic risk beta turns out to be sufficient. [11]

Generally, it has been shown that network components substantially increase the overall performance of individual Value-at-Risk models in terms of resulting backtest p-values (Hautsch, Schaumburg, and Schienle (2015), Hautsch, Schaumburg, and Schienle (2014)). Moreover, if macroeconomic and balance sheet characteristics of financial institutions are data-drivenly penalized, they are often de-selected by the LASSO procedure when controlling for tail network effects, which themselves are determined as highly significant (see Hautsch, Schaumburg, and Schienle (2015)). We find that the inclusion of sovereign tail effects helps to further augment the model fit for banks' idiosyncratic risk during the sovereign debt crisis. In particular, we obtain an 8.2% increase of the median backtest p-value across all crisis countries when comparing the model with included sovereign tail network effects to the model based on a network of financial institutions only.[12] Furthermore, network effects substantially contribute to the systemic risk beta. This is illustrated in Figure 9 for representative examples of each of the groups. In particular, for Dexia after 2011 and Santander, more than 90% of the final size of β results from interconnectedness. Thus network effects matter in both parts of the procedure and their impact on the final measure of systemic relevance is non-negligible.

[11] We have also experimented with alternative interconnectedness measures without obtaining systematically different results. This is due to the fact that in most periods, our measure is relatively highly correlated with alternative measures, such as PageRank or closeness.

[12] We use the likelihood ratio backtest for conditional VaR (see Berkowitz, Christoffersen, and Pelletier (2011)) and compare the median of in-sample p-values.

5 Conclusions

The paper provides a framework for estimating time-varying systemic risk contributions of financial entities and applies it to a comprehensive sample of large European banks. Our measure of realized systemic risk takes into account both the individual riskiness of the bank as well as the degree of price co-movement with the left tail of the financial system return distribution, which we refer to as marginal systemic relevance. Not surprisingly, we find that at the height of the sovereign debt crisis, banks from countries participating in the EU-IMF programme exhibit the greatest degree of systemic risk contributions. We document that marginal systemic relevance increases with size, leverage, and interconnectedness. Taking these factors into account, banks from programme countries rank highly in the distribution of realized systemic risk. However, there is a noticeable difference to the estimated systemic risk ranking during the global financial crisis with large, global banks ranking at the top.

The systemic risk contributions are based on tail dependence networks that can be used as monitoring tools and thus are an output of interest in their own right. We show that the network density varies with the intensity of the financial crisis. We further document that the fragmentation of the European financial system is reflected by a clustering of tail dependence relationships at the country level and provide evidence that fragmentation has peaked. Constructing the networks based on CDS spreads allow for a symmetric treatment of banks and sovereigns and for an explicit representation of bank-sovereign interactions. The tail dependence networks reveal a dramatic increase in the interdependence of banks and sovereigns since the beginning of the financial crisis. While there is evidence that bank-sovereign interaction has peaked, it is still way above the levels observed before the crisis.

We believe that our framework can be a useful monitoring device for policy makers. As it is based on asset prices and the procedure is highly data driven, the resulting tail dependence networks provide a market view on systemic risk relationships in the banking system. Such a market view provides a complementary perspective to networks based on contractual linkages between banks that are visible only by a supervisory authority. The systemic risk rankings can be likewise used for monitoring purposes. A consistently high ranking in any of the three risk metrics should trigger a supervisory follow-up. We caution against mechanically tying the systemic risk measure to a regulatory measure such as a capital surcharge as advocated by (Acharya, Engle, and Richardson 2012). The systemic risk ranking produced by our methodology can feed into the regulatory process, a measure such as a capital surcharge for systemically relevant financial institutions should be, however, based on a broader set of indicators and considerations.

Appendix

Selection algorithm for relevant risk drivers

We adapt the data-driven procedure of Hautsch, Schaumburg, and Schienle (2015) to account for time-variation in tail risk networks and different types and scalings of potential risk drivers. Determination of relevant risk drivers $R^{(i,t_0)}$ at the beginning of a year t_0 uses information of observations from the previous two years on a rolling window basis. Hence, it is based on approximately $\tau = 500$ observations $R_{t_0-\tau}, \ldots, R_{t_0-1}$, where each R_t is a K-vector of centered observations of the potential regressors. The idea is to use penalized quantile regression of LASSO-type for model selection and then to re-estimate the resulting model to obtain unbiased coefficient estimates (see Belloni and Chernozhukov (2011)). Due to the included sovereigns we modify the procedure in the post-LASSO selection step into a weighted LASSO for quantiles by introducing data-driven weights w_k^{i,t_0} for different components $R_{t,k}$. We thus obtain an improved precision in the selection step (see Wu and Liu (2009)).

The whole methodology works in 3 steps for each institution i in the system at time point t_0:

Step 1: Determine the penalty parameter λ^{i,t_0} and the component-specific weights w^{i,t_0} from the data:

Step a) Take τ iid draws from $\mathcal{U}[0,1]$ independent of $R_{t_0-\tau}, \ldots, R_{t_0-1}$ denoted as $U_1, \ldots, U_\tau$. Conditional on observations of R, calculate the corresponding value of the random variable,

$$\Lambda^{i,t_0} = \tau \max_{1 \leq k \leq K} \frac{1}{\tau} \left| \sum_{t=1}^{\tau} \frac{R_{t_0-t,k}(q - I(U_t \leq q))}{\hat{\sigma}_k \sqrt{q(1-q)}} \right| . \tag{8}$$

Step b) Repeat step a) B=500 times generating the empirical distribution of Λ^{i,t_0} conditional on R through $\Lambda_1^{i,t_0}, \ldots, \Lambda_B^{i,t_0}$. For a confidence level $\alpha \leq 1/K$ in the selection, set

$$\lambda^{i,t_0} = c \cdot Q(\Lambda^{i,t_0}, 1-\alpha | R_{t_0}-), \tag{9}$$

where $Q(\Lambda^{i,t_0}, 1-\alpha|R_{t_0}-)$ denotes the $(1-\alpha)$-quantile of Λ^{i,t_0} given $R_{t_0-\tau}, \ldots, R_{t_0-1}$ and $c \leq 2$ is a constant. Choose $\alpha = 0.1$ for optimal rates of the post-penalization estimators as in Belloni and Chernozhukov (2011). Generate $\lambda^{i,t_0}(c)$ for different parameter values c on an equi-distant grid.

Step c) Run an unrestricted quantile regression to obtain weights w_i for the penalization

$$\breve{\alpha}_q^{i,t_0} = \text{argmin}_{\alpha^i} \frac{1}{\tau} \sum_{t=1}^{\tau} \rho_q \left(X_{t_0-t}^i + \alpha^i R_{t_0-t} \right) . \tag{10}$$

Set $w_k^{i,t_0} = |\breve{\alpha}_{q,k}^{i,t_0}|^{-\gamma}$ with $\gamma > 0$. Generate $w^{i,t_0}(\gamma) = (w_1^{i,t_0}(\gamma), \ldots, w_K^{i,t_0}(\gamma))'$ on an equi-distant grid of different γ.

Step 2: Run an l_1-penalized quantile regression and calculate for each $(\lambda^{i,t_0}(c); w^{i,t_0}(\gamma))$ on the pairwise grid (c,γ) of step 1,

$$\widetilde{\alpha}_q^{i,t_0} = \text{argmin}_{\alpha^i} \frac{1}{\tau} \sum_{t=1}^{\tau} \rho_q \left(X^i_{t_0-t} + \alpha^i R_{t_0-t} \right) + \lambda^{i,t_0}(c) \frac{\sqrt{q(1-q)}}{\tau} \sum_{k=1}^{K} w_k^{i,t_0} \hat{\sigma}_k |\alpha^i_k| \,, \tag{11}$$

with the set of potentially relevant regressors $R_t = (R_{t,k})_{k=1}^K$, componentwise variation $\hat{\sigma}_k^2 = \frac{1}{\tau}\sum_{t=1}^{\tau}(R_{t_0-t,k})^2$ and the loss function $\rho_q(u) = u(q - I(u<0))$, where the indicator $I(\cdot)$ is 1 for $u<0$ and zero otherwise.

Step 3: Drop all firms in R with absolute marginal effects $|\widetilde{\alpha}^{i,t_0}(c,\gamma)|$ below a threshold $a = 0.0001$ keeping only the $K(i,t_0)$ remaining relevant regressors $R^{(i,t_0)}(c,\gamma)$. Re-estimate the unrestricted model (11) without penalty only with the selected relevant regressors $R^{(i,t_0)}(c,\gamma)$. This regression yields the post-LASSO estimates $\widehat{\alpha}_q^{i,t_0}(c,\gamma)$. The final estimates are the ones which maximize the in-sample predictive ability of the resulting VaR specification jointly in c and γ. This is evaluated according to a backtest criterion (see Berkowitz, Christoffersen, and Pelletier (2011)).

Tables and Figures

			Stock returns (daily)		CDS returns (daily)	
Name	ID	Country	Mean	Std.Dev.	Mean	Std.Dev.
Allied Irish Banks	alb	ie	-1.27e-03	0.060		
Alpha Bank	alp	gr	-3.20e-04	0.048		
BBVA	bbv	es	-1.83e-04	0.024	3.08e-03	0.049
BNP Paribas	bnp	fr	1.48e-04	0.030	2.95e-03	0.052
Banca Carige	crg	it	-4.49e-04	0.021		
Banca Popolare di Milano	pmi	it	-8.39e-04	0.030	2.61e-03	0.039
Bance Popolare dell'Emilia Romagna	bpe	it	-3.94e-04	0.025		
Banco BPI	bpi	pt	-6.41e-04	0.025		
Banco Comercial Portugues	bcp	pt	-1.01e-03	0.027	3.00e-03	0.043
Banco Popolare SC	bpi	it	-1.28e-03	0.033	2.46e-03	0.045
Banco Popular Espanol	pop	es	-1.11e-03	0.025	3.22e-03	0.057
Banco Santander	san	es	-1.20e-04	0.025	2.99e-03	0.050
Banco de Sabadell	sab	es	-6.18e-04	0.019	2.67e-03	0.038
Bank of Cyprus	boc	cy	-1.18e-03	0.035		
Bank of Ireland	bki	ie	-4.51e-04	0.059	3.37e-03	0.050
Bankinter	bkt	es	-1.14e-04	0.026		
Barclays	bar	gb	3.46e-04	0.040	2.84e-03	0.051
Commerzbank	cbk	de	-1.17e-03	0.035	2.64e-03	0.052
Credit Agricole	aca	fr	-2.50e-04	0.032	2.89e-03	0.049
Credit Industriel et Commerciale	ccf	fr	-1.44e-04	0.016		
Danske Bank	dan	dk	-1.05e-04	0.025	2.73e-03	0.050
Deutsche Bank	dbk	de	-8.18e-05	0.029	2.39e-03	0.050
Deutsche Postbank	dpb	de	2.28e-05	0.025		
Dexia	dex	be	-1.38e-03	0.069		
EFG Eurobank	eur	gr	-8.77e-04	0.056		
Erste Group Bank	ebs	at	1.56e-04	0.034	2.27e-03	0.046
Espirito Santo Financial Group	esf	pt	-6.96e-04	0.013	2.97e-03	0.044
HSBC	hsb	gb	9.22e-05	0.020	2.58e-03	0.048
ING	ing	nl	2.80e-05	0.037	2.61e-03	0.044
Intesa Sanpaolo	isp	it	-2.47e-04	0.029	3.64e-03	0.065
Irish Life and Permanent	ipm	ie	-5.09e-04	0.077		
KBC	kbc	be	2.90e-04	0.042		
Landesbank Berlin	beb	de	1.88e-04	0.022		
Lloyds	llo	gb	1.08e-05	0.040	2.88e-03	0.047
Marfin	cpb	cy	-1.69e-03	0.037		
Monte dei Paschi	bmp	it	-1.16e-03	0.028	3.29e-03	0.049
National Bank of Greece	ete	gr	-1.05e-03	0.046		
Natixis	knf	fr	-4.17e-05	0.037	1.96e-03	0.038
Nordea	nda	se	3.30e-04	0.024	2.43e-03	0.077
OTP Bank	otp	hu	2.82e-04	0.029		
Piraeus	tpe	gr	-1.09e-03	0.049		
Pohjola	poh	fi	4.26e-04	0.025		
Powszechna Kasa	pko	pl	2.71e-04	0.022		
Royal Bank of Scotland	rbs	gb	-5.70e-04	0.042	3.08e-03	0.050
SEB	seb	se	2.79e-04	0.030	2.66e-03	0.056
Societe Generale	gle	fr	-1.79e-04	0.033	2.88e-03	0.048
Standard Chartered	sta	gb	5.27e-04	0.028	1.56e-03	0.039
Svenska Handelsbanken	shb	se	4.46e-04	0.021	2.12e-03	0.071
Swedbank	swe	se	4.39e-04	0.030		
UniCredit	ucg	it	-6.54e-04	0.033	3.00e-03	0.051
Unione di Banche Italiane	ubi	it	-7.28e-04	0.025		

Table 1: Banks in the sample

	Bond yields (first diff.; daily)		CDS returns (daily)	
Country	Mean	Std.Dev.	Mean	Std.Dev.
AT	-1.06e-03	0.05	3.73e-03	0.07
BE	-7.87e-04	0.05		
DE	-1.28e-03	0.05	4.43e-03	0.09
DK	-1.23e-03	0.09	9.76e-04	0.04
ES	3.72e-04	0.08	4.26e-03	0.06
FI	-1.14e-03	0.06		
FR	-9.51e-04	0.05	7.22e-03	0.12
GB	-1.25e-03	0.05	1.47e-03	0.04
GR	3.61e-03	0.84		
HU	-1.01e-03	0.14		
IE	1.21e-05	0.10	1.58e-02	0.58
IT	9.64e-05	0.07	2.80e-03	0.05
NL	-1.05e-03	0.04	2.34e-03	0.05
PL	-7.24e-04	0.06		
PT	1.24e-03	0.14	3.60e-03	0.06
SE	-1.00e-03	0.05	2.32e-03	0.05

Table 2: Summary statistics sovereigns

	(1) Network density	(2) Share of domestic linkages
2006	0.07	0.34
2007	0.07	0.37
2008	0.08	0.28
2009	0.06	0.47
2010	0.04	0.52
2011	0.05	0.45

The table shows how network density and the fragmentation as represented by the share of domestic linkages evolve over time. The networks result from the LASSO selection procedure as described above and are based on six (overlapping) two-year periods. The networks are based on non-penalized control variables including bank-specific characteristics, macro-financial state variables and sovereign bond yields.

Table 3: Characteristics of estimated tail dependence networks based on equity returns of 51 European banks, 2006-2013.

	(1) Crisis countries	(2) Non-crisis countries
2006	0.32	0.10
2007	0.35	0.17
2008	0.20	0.15
2009	0.45	0.25
2010	0.56	0.30
2011	0.44	0.17

The table presents the share of domestic linkages between banks of a given country. In the case of AT, DK, FI, HU, NL, and PL, there is just one bank in the sample so the quantity is not defined. The column "crisis countries" refers to the simple average for a group of countries composed of CY, ES, GR, IE, IT, and PT. "Non-crisis countries" refers to the average over all other countries in the sample. The networks result from the LASSO selection procedure as described above and are based on six (overlapping) two-year periods. The networks are based on non-penalized control variables including bank-specific characteristics, macro-financial state variables and sovereign bond yields.

Table 4: Share of domestic linkages in estimated tail dependence networks based on equity returns of 51 European banks, 2006-2013.

	(1) Network density	(2) Share of domestic linkages	(3) Share of sovereign bank linkages
2006	0.13	0.22	0.01
2007	0.14	0.20	0.06
2008	0.18	0.20	0.10
2009	0.12	0.30	0.13
2010	0.17	0.32	0.21
2011	0.18	0.23	0.19

The table shows how network density, the fragmentation as represented by the share of domestic linkages, and sovereign bank interaction evolve over time. The share of domestic linkages only takes into account connections between banks. The networks result from the LASSO selection procedure as described above and are based on six (overlapping) two-year periods. The networks are based on non-penalized macro-financial state variables when modeling the VaR of banks and sovereigns.

Table 5: Characteristics of estimated tail dependence networks based on CDS returns of 29 European banks and 11 sovereigns, 2006-2013.

	(1) Crisis countries	(2) Non-crisis countries
2006	1.25	1.33
2007	4.25	4.86
2008	5.25	4.71
2009	5.75	5.29
2010	9.00	7.43
2011	7.00	5.00

The table presents the interconnectedness of sovereigns as represented by degree. The column "crisis countries" refers to the simple average for a group of countries composed of CY, ES, GR, IE, IT, and PT. "Non-crisis countries" refers to the average over all other countries in the sample. The networks result from the LASSO selection procedure as described above and are based on six (overlapping) two-year periods. The networks are based on non-penalized macro-financial state variables when modeling the VaR of banks and sovereigns.

Table 6: Sovereign interconnectedness by degree

	(1) Crisis countries	(2) Non-crisis countries
2006	0.00	0.25
2007	0.28	0.07
2008	0.19	0.20
2009	0.26	0.13
2010	0.35	0.24
2011	0.46	0.33

The table presents the share of linkages between sovereigns and banks. The column "crisis countries" refers to the simple average for a group of countries composed of CY, ES, GR, IE, IT, and PT. "Non-crisis countries" refers to the average over all other countries in the sample. The networks result from the LASSO selection procedure as described above and are based on six (overlapping) two-year periods. The networks are based on non-penalized macro-financial state variables when modeling the VaR of banks and sovereigns.

Table 7: Share of linkages between sovereign and banks

Rank	Bank name	ID	Country	**Realized systemic risk β**	Systemic risk β	$\widehat{VaR}$
1	Irish Life and Permanent	ipm	ie	**0.0193**	0.1345	0.1432
2	Bank of Cyprus	boc	cy	**0.0136**	0.2125	0.0639
3	National Bank of Greece	ete	gr	**0.0131**	0.1160	0.1129
4	Dexia	dex	be	**0.0121**	0.1583	0.0766
5	Alpha Bank	alp	gr	**0.0100**	0.1863	0.0539
6	Royal Bank of Scotland	rbs	gb	**0.0095**	0.2259	0.0423
7	Banca Carige	crg	it	**0.0088**	0.1059	0.0830
8	Barclays	bar	gb	**0.0082**	0.2557	0.0322
9	Marfin	cpb	cy	**0.0075**	0.1415	0.0530
10	Natixis	knf	fr	**0.0073**	0.2593	0.0281
11	OTP Bank	otp	hu	**0.0072**	0.2582	0.0279
12	KBC	kbc	be	**0.0066**	0.1355	0.0486
13	Bankinter	bkt	es	**0.0063**	0.1530	0.0411
14	Lloyds	llo	gb	**0.0062**	0.1741	0.0355
15	Piraeus	tpe	gr	**0.0062**	0.1416	0.0437
16	EFG Eurobank	eur	gr	**0.0061**	0.1399	0.0433
17	Bank of Ireland	bki	ie	**0.0059**	0.1624	0.0361
18	Bance Popolare dell'Emilia Romagna	bpe	it	**0.0055**	0.1528	0.0362
19	Commerzbank	cbk	de	**0.0054**	0.1532	0.0356
20	Credit Agricole	aca	fr	**0.0053**	0.2484	0.0214
21	Danske Bank	dan	dk	**0.0049**	0.2052	0.0236
22	Erste Group Bank	ebs	at	**0.0049**	0.2024	0.0241
23	Intesa Sanpaolo	isp	it	**0.0049**	0.1980	0.0247
24	Credit Industriel et Commerciale	ccf	fr	**0.0046**	0.2269	0.0202
25	Banco Santander	san	es	**0.0044**	0.2278	0.0193
26	Banco Comercial Portugues	bcp	pt	**0.0042**	0.0882	0.0472
27	UniCredit	ucg	it	**0.0042**	0.2134	0.0195
28	BBVA	bbv	es	**0.0041**	0.2498	0.0164
29	SEB	seb	se	**0.0040**	0.2319	0.0173
30	Monte dei Paschi	bmp	it	**0.0039**	0.0907	0.0435
31	ING	ing	nl	**0.0039**	0.1714	0.0229
32	Standard Chartered	sta	gb	**0.0038**	0.2003	0.0191
33	Deutsche Bank	dbk	de	**0.0036**	0.1696	0.0215
34	Societe Generale	gle	fr	**0.0035**	0.1687	0.0206
35	BNP Paribas	bnp	fr	**0.0034**	0.1766	0.0194
36	Banco Popular Espanol	pop	es	**0.0034**	0.1163	0.0288
37	Banco BPI	bpi	pt	**0.0033**	0.1226	0.0266
38	Unione di Banche Italiane	ubi	it	**0.0029**	0.1226	0.0238
39	Banco Popolare SC	bpi	it	**0.0028**	0.1207	0.0228
40	Allied Irish Banks	alb	ie	**0.0027**	0.0416	0.0646
41	Nordea	nda	se	**0.0026**	0.2133	0.0124
42	Pohjola	poh	fi	**0.0026**	0.1784	0.0145
43	Swedbank	swe	se	**0.0026**	0.1787	0.0145
44	Banca Popolare di Milano	pmi	it	**0.0021**	0.1014	0.0209
45	Deutsche Postbank	dpb	de	**0.0020**	0.1355	0.0150
46	HSBC	hsb	gb	**0.0020**	0.2330	0.0087
47	Banco de Sabadell	sab	es	**0.0018**	0.1425	0.0124
48	Svenska Handelsbanken	shb	se	**0.0018**	0.1985	0.0090
49	Powszechna Kasa	pko	pl	**0.0015**	0.1003	0.0146
50	Landesbank Berlin	beb	de	**0.0012**	0.1211	0.0100
51	Espirito Santo Financial Group	esf	pt	**0.0007**	0.0863	0.0077

The table ranks banks according to realized systemic risk in June 2012. Realized systemic risk is given by the product of systemic risk beta and value-at-risk as in Equation (7).

Table 8: Realized systemic risk of 51 European banks, June 2012

Bank name	Systemic risk β	Group	Size	Leverage	Net
Natixis	0.2593	3	6.2299	26.1202	1.3863
OTP Bank	0.2582	1	3.5264	7.3755	1.7918
Barclays	0.2557	3	7.5333	29.0104	1.0986
BBVA	0.2498	3	6.3977	15.3705	1.0986
Credit Agricole	0.2484	3	7.4519	36.1905	1.0986
HSBC	0.2330	2	7.5899	15.9292	1.0986
SEB	0.2319	3	5.5769	21.7143	1.0986
Banco Santander	0.2278	2	7.1572	16.8518	1.3863
Credit Industriel et Commerciale	0.2269	3	5.4523	25.2925	1.0986
Royal Bank of Scotland	0.2259	2	7.4282	19.0981	1.0986
UniCredit	0.2134	2	6.8385	14.5713	0.6931
Nordea	0.2133	3	6.5425	25.9949	0.6931
Bank of Cyprus	0.2125	1	3.6547	15.1471	1.0986
Danske Bank	0.2052	3	6.1540	28.4674	0.6931
Erste Group Bank	0.2024	3	5.3786	17.7028	0.6931
Standard Chartered	0.2003	2	6.1254	13.7613	0.6931
Svenska Handelsbanken	0.1985	3	5.6288	26.9227	0.6931
Intesa Sanpaolo	0.1980	2	6.4810	12.4980	0.0000
Alpha Bank	0.1863	1	4.0530	15.8155	1.0986
Swedbank	0.1787	2	5.3662	19.1752	0.6931
Pohjola	0.1784	1	3.7527	17.0224	0.6931
BNP Paribas	0.1766	3	7.5834	28.0491	0.0000
Lloyds	0.1741	3	7.0558	21.4171	0.0000
ING	0.1714	3	7.1243	25.8275	0.0000
Deutsche Bank	0.1696	3	7.6513	37.5956	0.0000
Societe Generale	0.1687	3	7.0850	28.3256	0.0000
Bank of Ireland	0.1624	2	5.0427	18.3763	0.0000
Dexia	0.1583	3	6.0229	21.4107	0.0000
Commerzbank	0.1532	3	6.5382	36.8333	0.0000
Bankinter	0.1530	2	4.1047	19.6879	0.6931
Bance Popolare dell'Emilia Romagna	0.1528	1	4.0969	16.1703	0.6931
Banco de Sabadell	0.1425	1	4.6570	14.8263	1.0986
Piraeus	0.1416	1	3.8606	3.3544	0.6931
Marfin	0.1415	1	3.4617	15.3970	0.0000
EFG Eurobank	0.1399	1	4.2985	2.1094	1.0986
Deutsche Postbank	0.1355	3	5.3287	35.8836	0.0000
KBC	0.1355	2	5.6721	59.4140	0.6931
Irish Life and Permanent	0.1345	2	4.2772	28.7822	0.0000
Banco BPI	0.1226	2	3.8012	39.6606	0.6931
Unione di Banche Italiane	0.1226	1	4.8791	12.7310	1.0986
Landesbank Berlin	0.1211	2	4.9002	49.8018	0.0000
Banco Popolare SC	0.1207	1	4.9048	12.6513	1.0986
Banco Popular Espanol	0.1163	1	5.0639	15.7241	1.0986
National Bank of Greece	0.1160	1	4.6453	2.1094	1.0986
Banca Carige	0.1059	1	3.8607	11.6481	0.0000
Banca Popolare di Milano	0.1014	1	3.9705	13.1303	0.0000
Powszechna Kasa	0.1003	1	3.8250	7.9325	0.0000
Monte dei Paschi	0.0907	1	5.4412	15.9840	1.0986
Banco Comercial Portugues	0.0882	1	4.5221	24.7166	0.0000
Espirito Santo Financial Group	0.0863	2	4.4446	70.8370	0.0000
Allied Irish Banks	0.0416	1	4.9174	15.7617	0.0000

The table ranks banks according to their systemic risk beta in June 2012. Systemic risk beta is a function of size, leverage and interconnectedness as represented by $log(outdegree + 1)$. Group refers to the grouping applied in the estimation of Equation (5). Banks in group 3 have above median size and leverage, while banks in group 1 have below median size and leverage. The remaining banks constitute group 2.

Table 9: Systemic risk betas and driving components, June 2012

Rank	Bank name	ID	Country	**Realized systemic risk β**	Systemic risk β	$\widehat{VaR}$
1	Dexia	dex	be	**0.0362**	0.2446	0.1479
2	Bank of Ireland	bki	ie	**0.0316**	0.1759	0.1795
3	Royal Bank of Scotland	rbs	gb	**0.0290**	0.2307	0.1257
4	Commerzbank	cbk	de	**0.0282**	0.2281	0.1235
5	KBC	kbc	be	**0.0280**	0.1927	0.1451
6	Credit Agricole	aca	fr	**0.0276**	0.2667	0.1037
7	Irish Life and Permanent	ipm	ie	**0.0275**	0.1445	0.1899
8	Barclays	bar	gb	**0.0268**	0.2057	0.1303
9	Societe Generale	gle	fr	**0.0253**	0.2619	0.0965
10	Lloyds	llo	gb	**0.0245**	0.2336	0.1051
11	Deutsche Postbank	dpb	de	**0.0245**	0.2100	0.1166
12	ING	ing	nl	**0.0243**	0.2114	0.1151
13	UniCredit	ucg	it	**0.0209**	0.1982	0.1056
14	Allied Irish Banks	alb	ie	**0.0208**	0.1553	0.1342
15	Standard Chartered	sta	gb	**0.0190**	0.1732	0.1097
16	SEB	seb	se	**0.0180**	0.1932	0.0932
17	OTP Bank	otp	hu	**0.0175**	0.1169	0.1500
18	Intesa Sanpaolo	isp	it	**0.0172**	0.1981	0.0868
19	BNP Paribas	bnp	fr	**0.0170**	0.1693	0.1004
20	Bank of Cyprus	boc	cy	**0.0162**	0.2279	0.0710
21	Erste Group Bank	ebs	at	**0.0160**	0.1464	0.1092
22	Banca Popolare di Milano	pmi	it	**0.0156**	0.2186	0.0713
23	Banco Santander	san	es	**0.0152**	0.2157	0.0705
24	Pohjola	poh	fi	**0.0150**	0.2023	0.0741
25	BBVA	bbv	es	**0.0149**	0.2807	0.0533
26	Piraeus	tpe	gr	**0.0148**	0.2355	0.0626
27	Deutsche Bank	dbk	de	**0.0143**	0.1521	0.0941
28	Svenska Handelsbanken	shb	se	**0.0139**	0.2433	0.0571
29	Swedbank	swe	se	**0.0131**	0.1752	0.0748
31	HSBC	hsb	gb	**0.0128**	0.2266	0.0566
30	Marfin	cpb	cy	**0.0128**	0.2066	0.0620
33	Alpha Bank	alp	gr	**0.0126**	0.1820	0.0694
32	Banco Popolare SC	bpi	it	**0.0126**	0.1441	0.0872
34	Powszechna Kasa	pko	pl	**0.0117**	0.2070	0.0566
35	National Bank of Greece	ete	gr	**0.0116**	0.1409	0.0822
36	Nordea	nda	se	**0.0111**	0.2370	0.0470
37	Banco Popular Espanol	pop	es	**0.0110**	0.2093	0.0524
38	Danske Bank	dan	dk	**0.0109**	0.1509	0.0725
40	Bance Popolare dell'Emilia Romagna	bpe	it	**0.0107**	0.1973	0.0544
39	Banco Comercial Portugues	bcp	pt	**0.0107**	0.1840	0.0579
41	Landesbank Berlin	beb	de	**0.0105**	0.1111	0.0946
42	Natixis	knf	fr	**0.0098**	0.1558	0.0627
43	Banca Carige	crg	it	**0.0089**	0.1838	0.0487
44	Banco BPI	bpi	pt	**0.0079**	0.1461	0.0542
45	EFG Eurobank	eur	gr	**0.0075**	0.1700	0.0437
46	Banco de Sabadell	sab	es	**0.0070**	0.2734	0.0258
47	Bankinter	bkt	es	**0.0069**	0.1547	0.0444
48	Unione di Banche Italiane	ubi	it	**0.0066**	0.1244	0.0527
49	Credit Industriel et Commerciale	ccf	fr	**0.0064**	0.2248	0.0286
50	Espirito Santo Financial Group	esf	pt	**0.0038**	0.0868	0.0438
51	Monte dei Paschi	bmp	it	**0.0032**	0.0697	0.0455

The table ranks banks according to realized systemic risk in October 2008. Realized systemic risk is given by the product of systemic risk beta and value-at-risk as in Equation (7).

Table 10: Realized systemic risk of 51 European banks, October 2008

Bank name	Systemic risk β	Group	Size	Leverage	Net
BBVA	0.2807	3	6.2305	20.1084	1.6094
Banco de Sabadell	0.2734	1	4.3880	17.2724	2.4849
Credit Agricole	0.2667	3	7.2895	36.5858	1.3863
Societe Generale	0.2619	3	6.9809	36.7140	1.3863
Dexia	0.2446	3	6.4347	47.3055	1.3863
Svenska Handelsbanken	0.2433	3	5.3006	28.2589	1.3863
Nordea	0.2370	3	6.0725	24.6836	1.0986
Piraeus	0.2355	1	3.9532	17.1094	1.6094
Lloyds	0.2336	3	6.1427	29.9180	1.0986
Royal Bank of Scotland	0.2307	2	7.6798	28.1315	1.7918
Commerzbank	0.2281	3	6.4220	41.5008	1.0986
Bank of Cyprus	0.2279	1	3.4521	15.8218	1.0986
HSBC	0.2266	2	7.3892	17.9267	1.0986
Credit Industriel et Commerciale	0.2248	3	5.5251	29.1889	1.0986
Banca Popolare di Milano	0.2186	1	3.8237	13.0968	1.3863
Banco Santander	0.2157	2	6.9010	18.9559	1.0986
ING	0.2114	3	7.2225	40.6074	0.6931
Deutsche Postbank	0.2100	3	5.4223	44.9140	1.0986
Banco Popular Espanol	0.2093	1	4.6937	16.6799	1.9459
Powszechna Kasa	0.2070	1	3.5589	9.5414	1.0986
Marfin	0.2066	1	3.5632	9.4828	1.0986
Barclays	0.2057	3	7.4546	51.6146	0.6931
Pohjola	0.2023	1	3.3490	15.1767	0.6931
UniCredit	0.1982	2	6.9658	20.2044	0.0000
Intesa Sanpaolo	0.1981	2	6.4484	11.9451	0.0000
Bance Popolare dell'Emilia Romagna	0.1973	1	3.9232	16.7478	1.0986
SEB	0.1932	3	5.4983	30.8818	0.6931
KBC	0.1927	2	5.9332	22.0918	1.0986
Banco Comercial Portugues	0.1840	1	4.5392	20.0341	1.3863
Banca Carige	0.1838	1	3.4222	8.8829	0.6931
Alpha Bank	0.1820	1	4.0538	13.8021	1.0986
Bank of Ireland	0.1759	2	5.2854	29.0040	1.3863
Swedbank	0.1752	2	5.1673	23.9362	1.0986
Standard Chartered	0.1732	2	5.4214	15.6492	0.0000
EFG Eurobank	0.1700	1	4.3495	17.7473	1.0986
BNP Paribas	0.1693	3	7.4351	34.0321	0.0000
Natixis	0.1558	3	6.2538	28.4809	0.0000
Allied Irish Banks	0.1553	1	5.1810	19.2902	1.6094
Bankinter	0.1547	2	3.9154	26.9901	1.6094
Deutsche Bank	0.1521	3	7.5993	57.4133	0.0000
Danske Bank	0.1509	3	6.1500	32.4465	0.0000
Erste Group Bank	0.1464	3	5.3648	23.5646	0.0000
Banco BPI	0.1461	2	3.7039	24.1041	1.0986
Irish Life and Permanent	0.1445	2	4.3828	31.1468	0.6931
Banco Popolare SC	0.1441	1	4.8677	12.0214	1.3863
National Bank of Greece	0.1409	1	4.5490	10.6437	1.0986
Unione di Banche Italiane	0.1244	1	4.7935	10.7961	1.0986
OTP Bank	0.1169	1	3.6267	9.2577	0.0000
Landesbank Berlin	0.1111	2	4.9886	59.4149	0.0000
Espirito Santo Financial Group	0.0868	2	4.3273	86.3160	1.3863
Monte dei Paschi	0.0697	1	5.3304	17.2038	0.6931

The table ranks banks according to their systemic risk beta in October 2008. Systemic risk beta is a function of size, leverage and interconnectedness as represented by $log(outdegree + 1)$. Group refers to the grouping applied in the estimation of Equation (5). Banks in group 3 have above median size and leverage, while banks in group 1 have below median size and leverage. The remaining banks constitute group 2.

Table 11: Systemic risk betas and driving components, October 2008

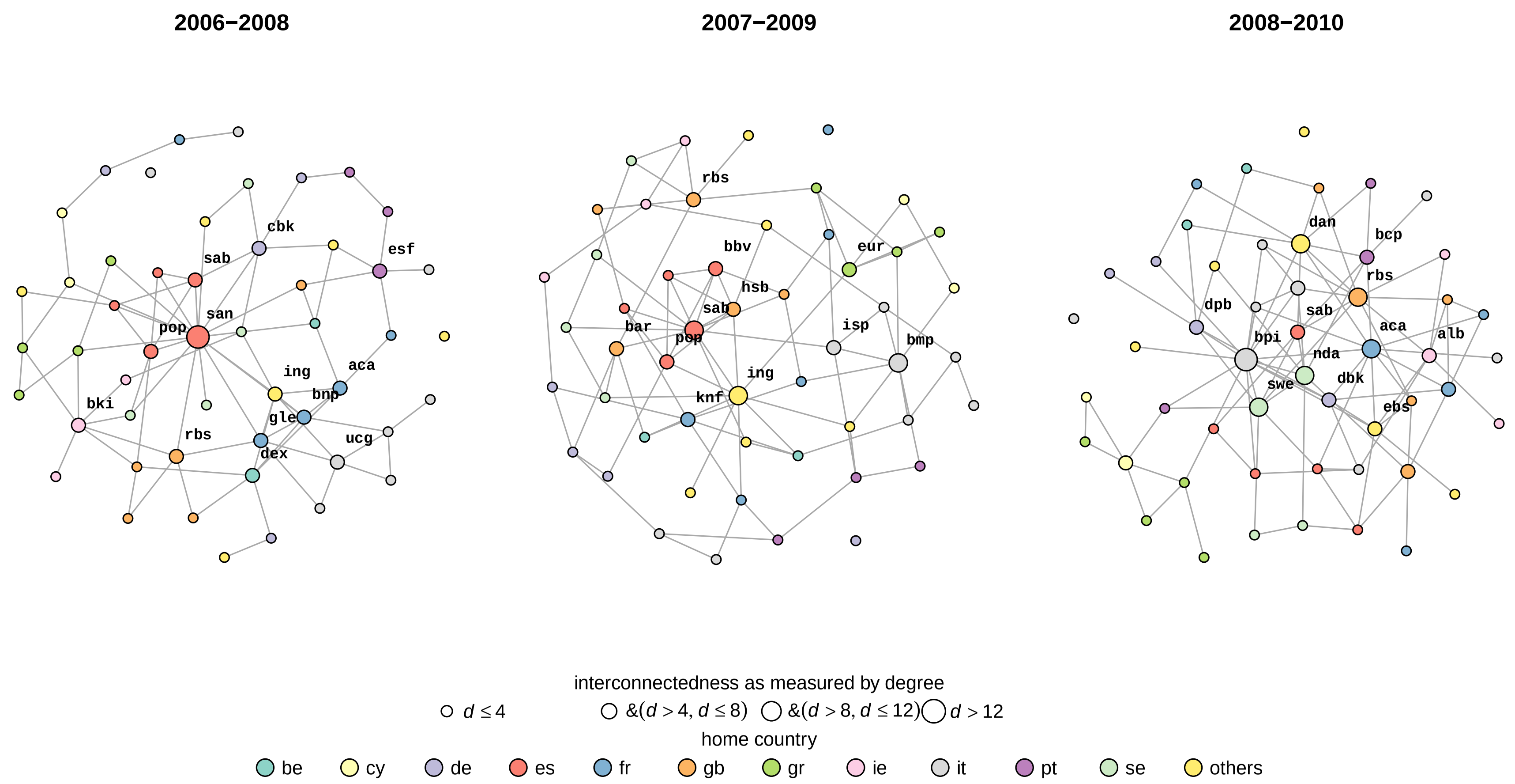

Figure 1: Time-varying tail dependence networks based on equity returns of 51 European banks, 2008-2010

The figure shows the evolution of tail dependence networks based on stock returns. Node size represents the interconnectedness of an entity as represented by degree. Node colour indicates the country where a bank is headquartered. Sovereign bond yields enter the specification as state variables that are not subject to penalization.

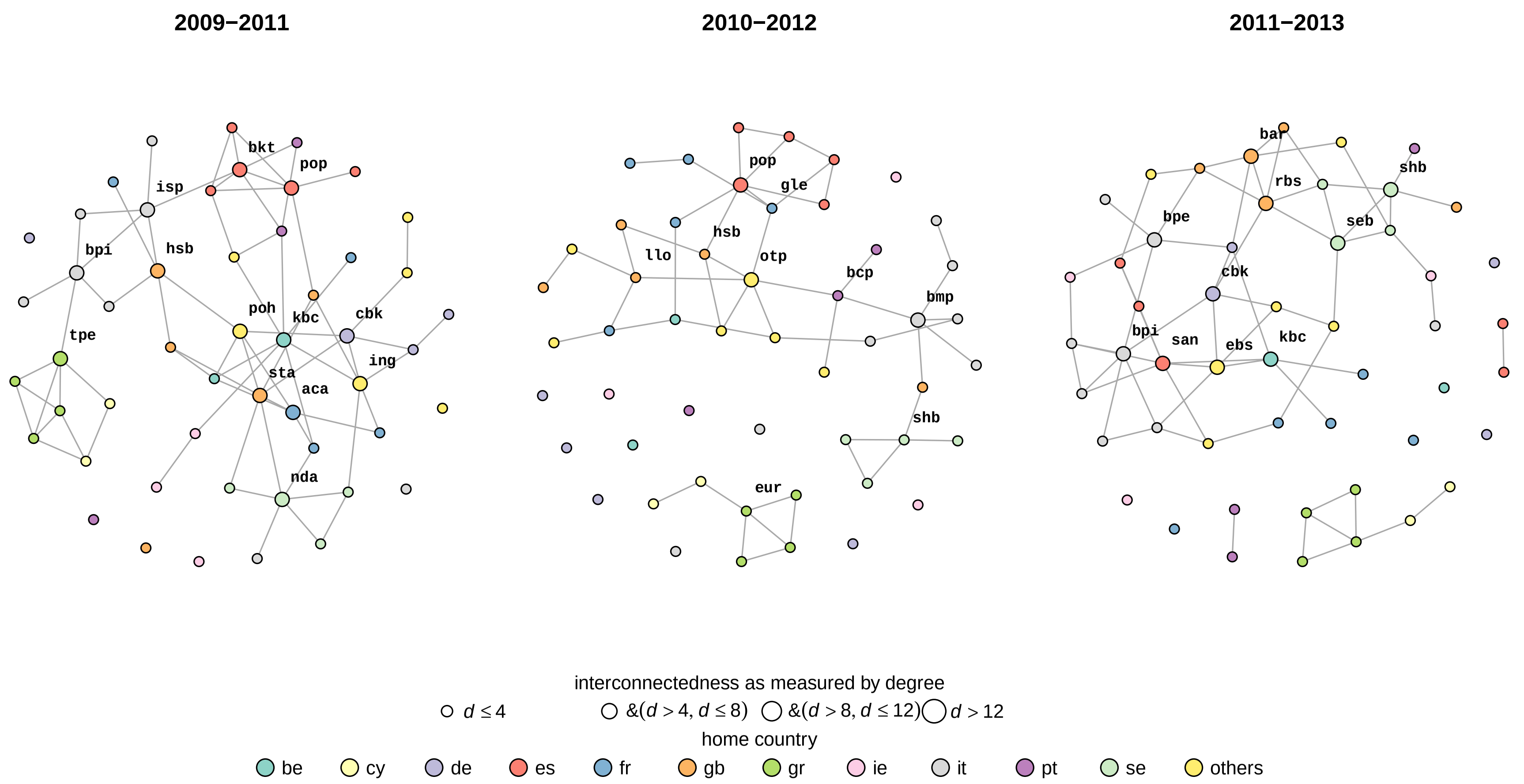

Figure 2: Time-varying tail dependence networks based on equity returns of 51 European banks, 2011-2013

The figure shows the evolution of tail dependence networks based on stock returns. Node size represents the interconnectedness of an entity as represented by degree. Node colour indicates the country where a bank is headquartered. Sovereign bond yields enter the specification as state variables that are not subject to penalization.

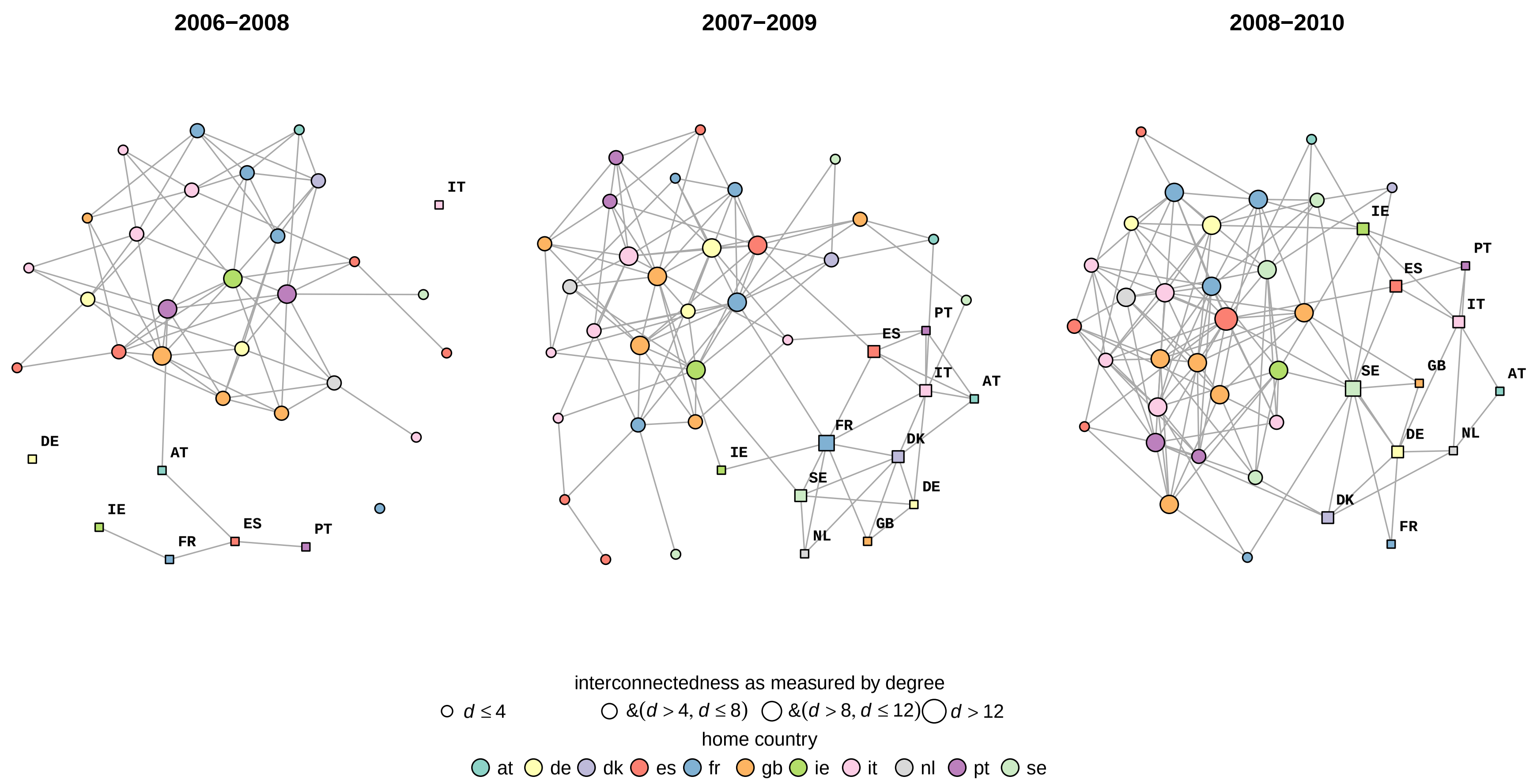

Figure 3: Time-varying tail dependence networks based on CDS returns of 29 European banks and 11 sovereigns, 2008-2010

The figure shows the evolution of tail dependence networks based on CDS returns. Round vertices represent banks and square vertices sovereigns. Node size represents the interconnectedness of an entity as represented by degree. Node colour indicates the country where a bank is headquartered.

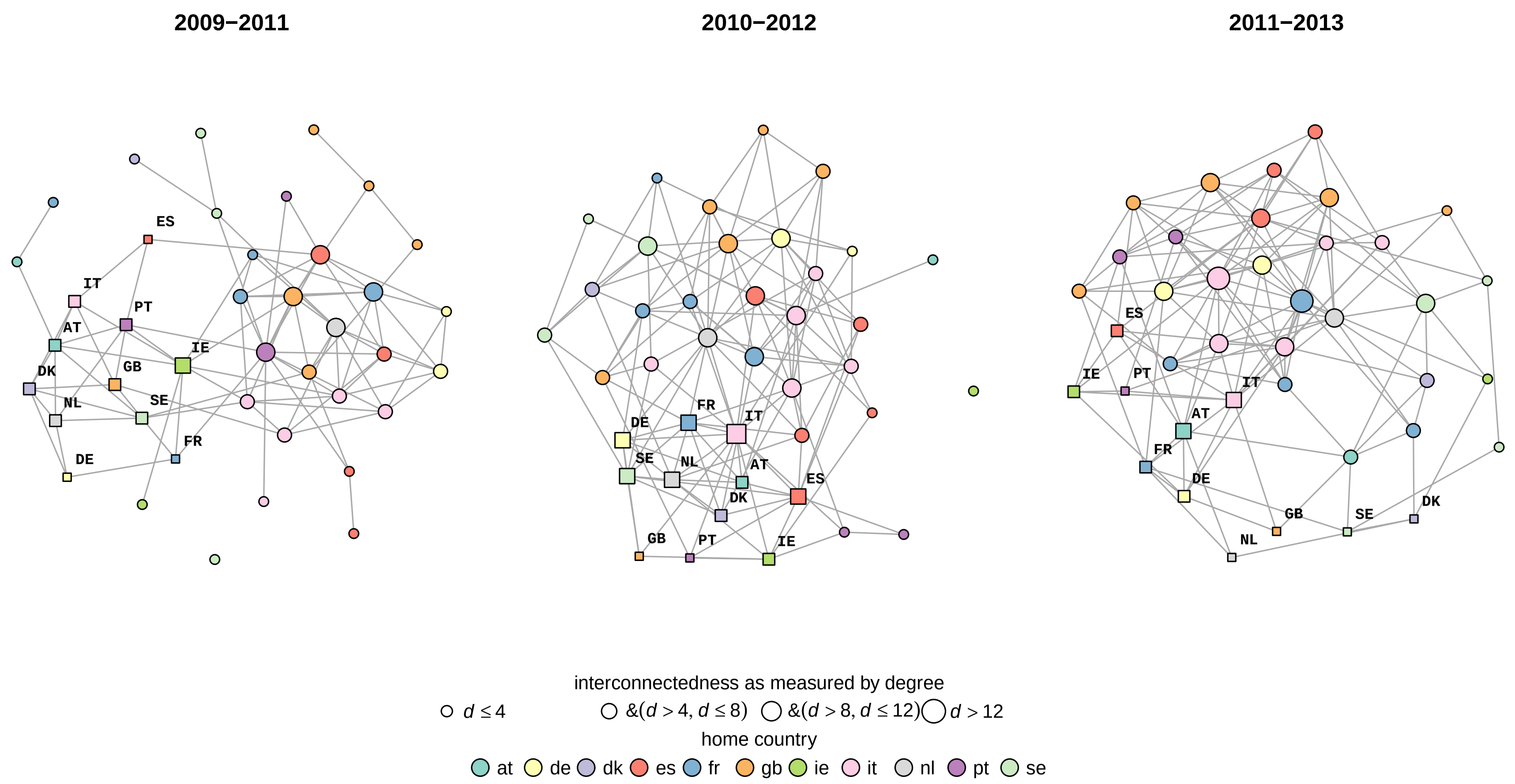

Figure 4: Time-varying tail dependence networks based on CDS returns of 29 European banks and 11 sovereigns, 2011-2013

The figure shows the evolution of tail dependence networks based on CDS returns. Round vertices represent banks and square vertices sovereigns. Node size represents the interconnectedness of an entity as represented by degree. Node colour indicates the country where a bank is headquartered.

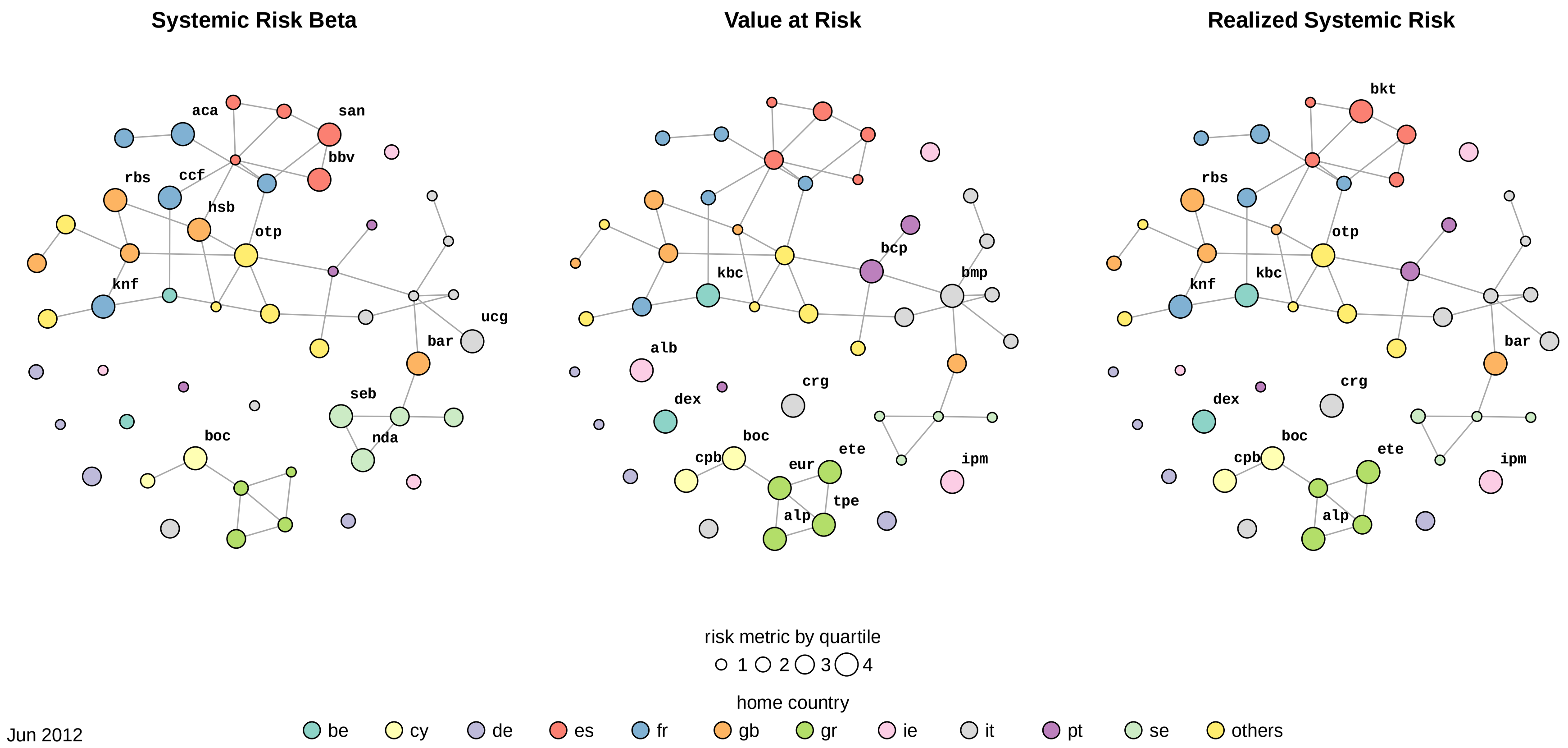

Figure 5: Systemic risk contributions and network structure based on equity returns of 51 European banks, June 2012

The figure compares the distributions of systemic risk beta, Value-at-Risk, and realized systemic risk in June 2012. For each distribution, node size indicates the quartile in which a bank ranks. Banks in the fourth quartile of each distribution are identified by their three letter ID as shown in Table 1. Node colour indicates the country where the bank is headquartered.

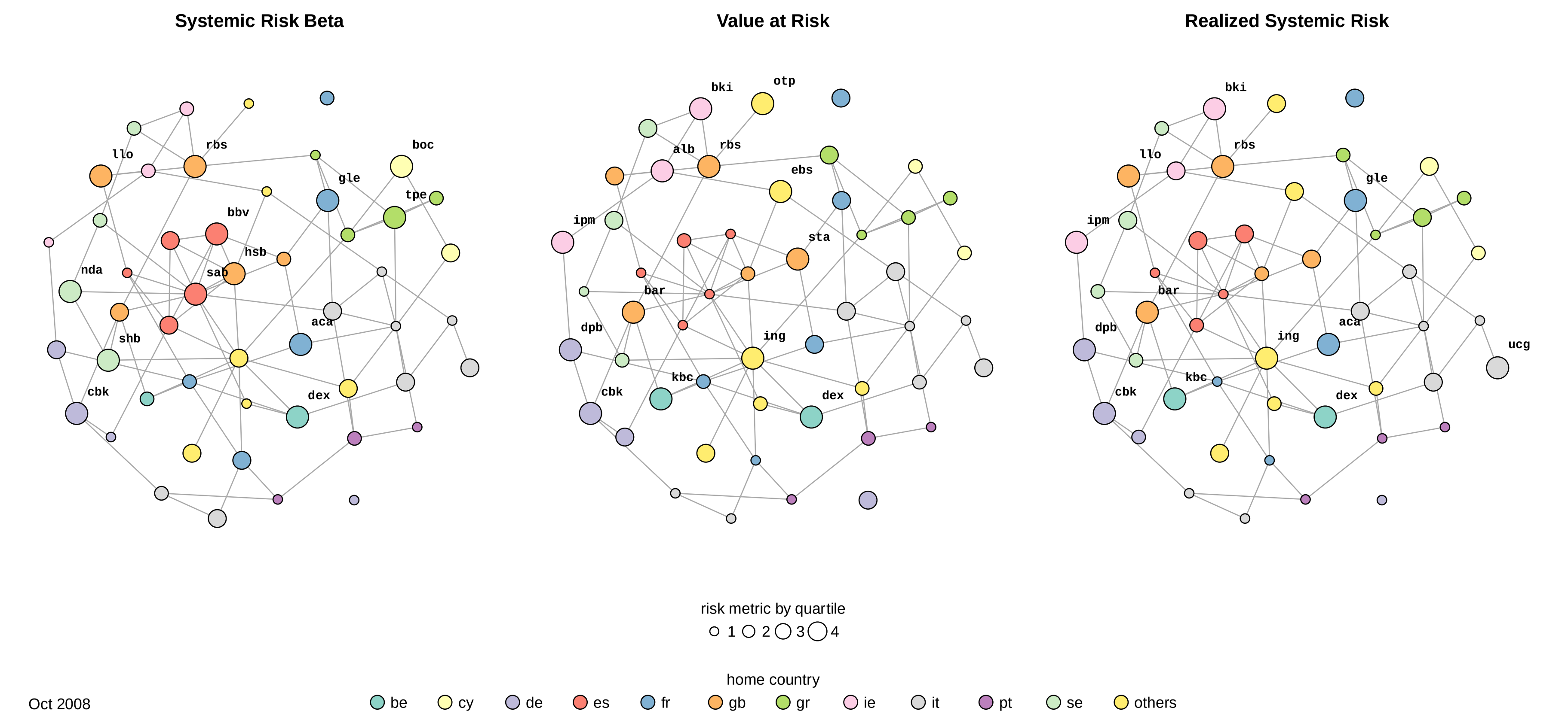

Figure 6: Systemic risk contributions and network structure based on equity returns of 51 European banks, October 2008

The figure compares the distributions of systemic risk beta, Value-at-Risk, and realized systemic risk in October 2008. For each distribution, node size indicates the quartile in which a bank ranks. Banks in the fourth quartile of each distribution are identified by their three letter ID as shown in Table 1. Node colour indicates the country where the bank is headquartered.

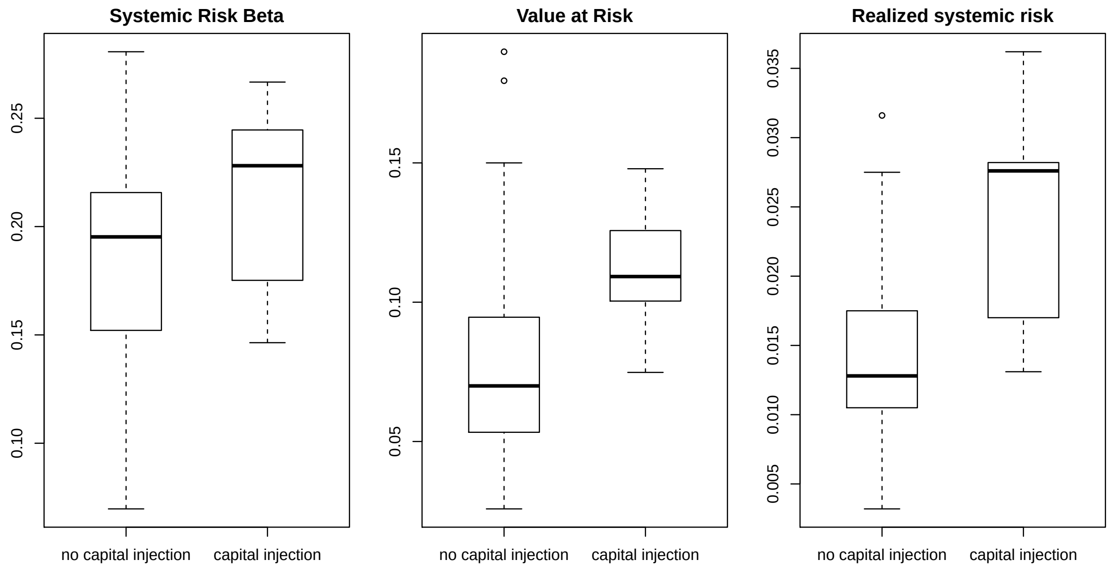

Figure 7: Risk metrics and capital injections, fourth quarter 2008

The figure compares the distributions of systemic risk beta, Value-at-Risk, and realized systemic risk conditional on whether a bank was re-capitalized in the fourth quarter of 2008.

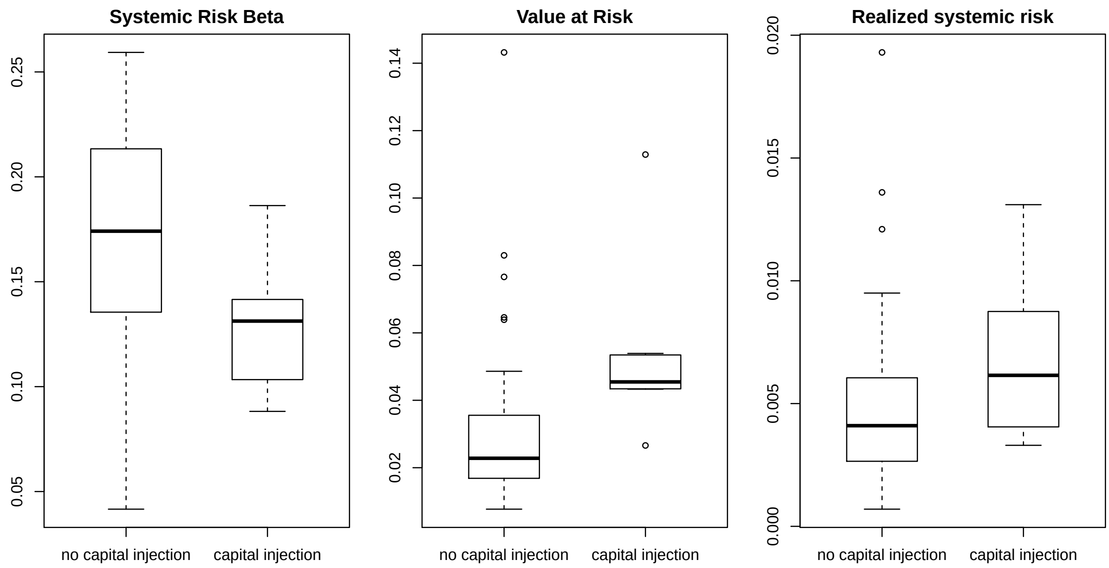

Figure 8: Risk metrics and capital injections, second quarter 2012

The figure compares the distributions of systemic risk beta, Value-at-Risk, and realized systemic risk conditional on whether a bank was recapitalized in the second quarter of 2012.

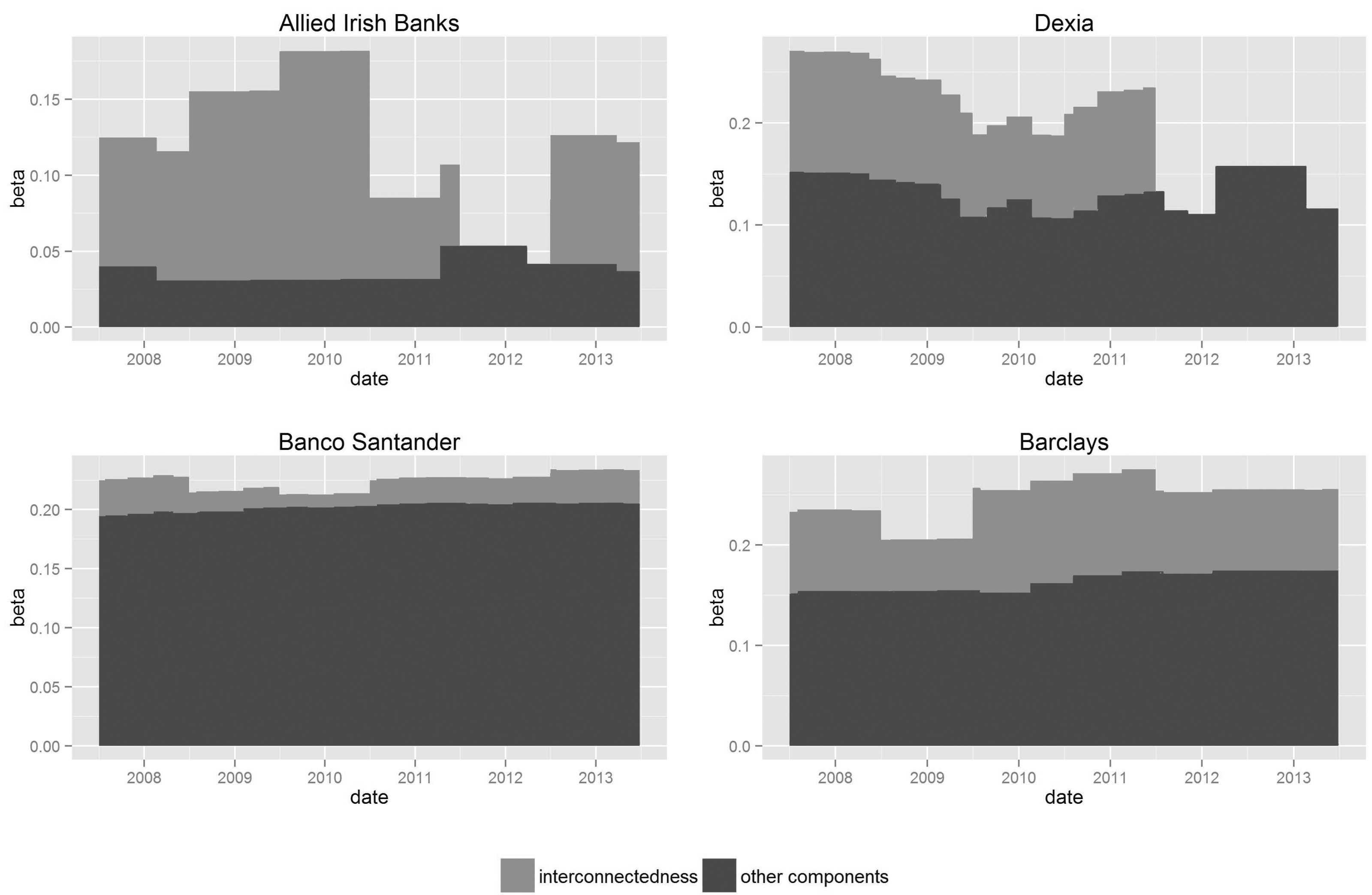

Figure 9: The time profile of systemic risk beta for selected sample banks

The figure shows the estimated systemic risk beta $\beta_g^{t_0}(B_t^i, net_t^{i,t_0})$ (abbreviated as beta in the graph), split up into its components $\delta_{2,g}^{t_0} net_t^{i,t_0}$ (”interconnectedness”), and $\delta_{0,g}^{t_0} + \delta_{1,g}^{t_0} B_t^i$ (”other components”) with B_t^i including size and leverage. At each point in time the level of the estimated systemic risk beta is given by the sum of the two components.

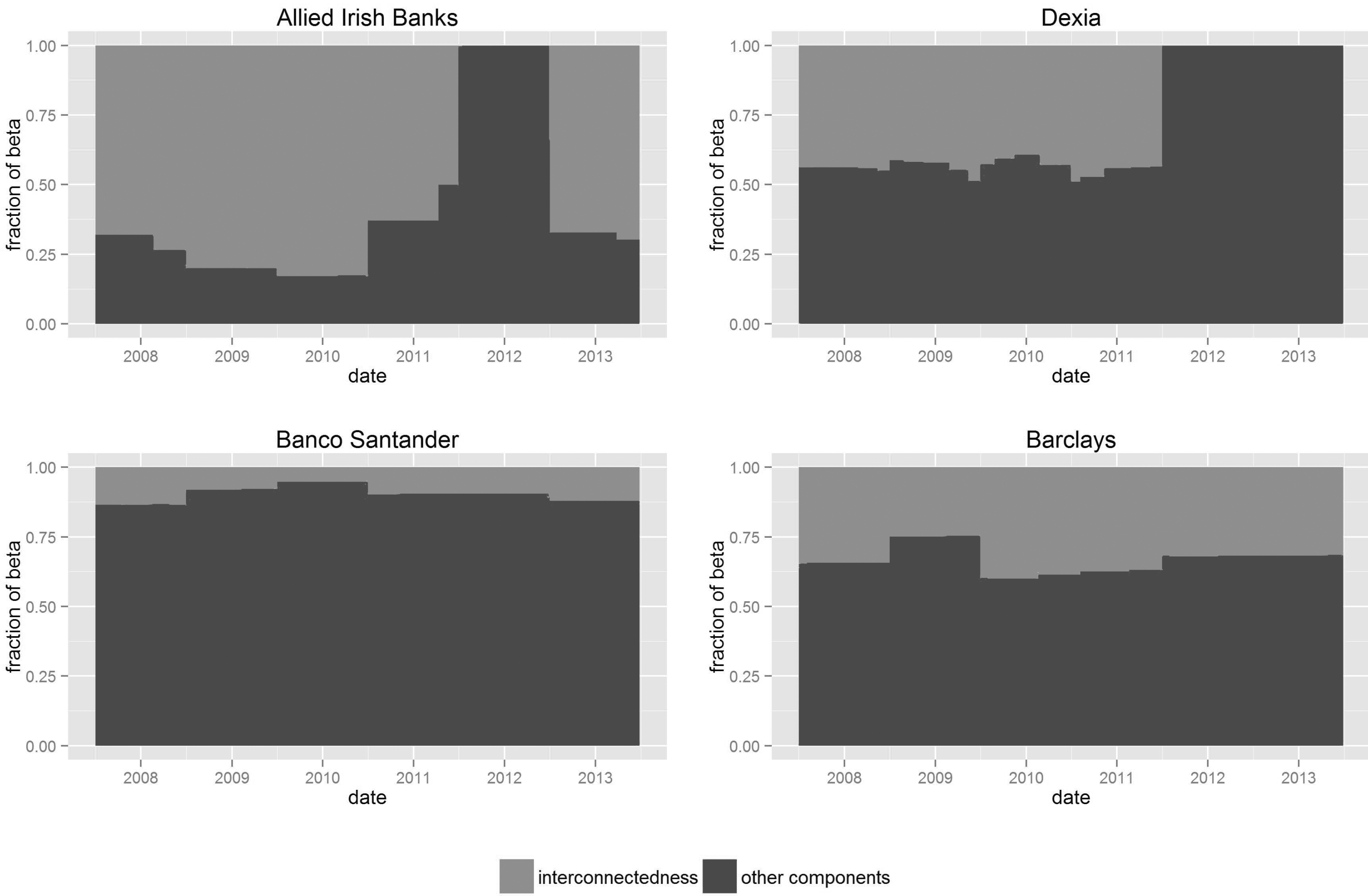

Figure 10: The composition of systemic risk beta for selected sample banks

The figure shows relative proportions $\delta_{2,g}^{t_0} net_t^{i,t_0}/\beta_g^{t_0}(.)$ (”interconnectedness”) and $(\delta_{0,g}^{t_0} + \delta_{1,g}^{t_0} B_t^i)/\beta_g^{t_0}(.)$ (”other components”) of the systemic risk beta (abbreviated as beta in the graph).

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