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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 network-driven time-varying systemic risk contributions that is applicable to a high-dimensional financial system. Tail risk dependencies and contributions are estimated based on a penalized two-stage fixed-effects quantile approach, which explicitly links bank interconnectedness to systemic risk contributions. The framework is applied to a system of 51 large European

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banks and 17 sovereigns through the period 2006 to 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 it is reflected in network statistics and systemic risk measures. Illustrating the usefulness of the framework as a monitoring tool, we provide indication for the fragmentation of the European financial system having peaked and that recovery has started.

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 clear 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 by for instance fire sales. The result of these 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 European sovereign debt crisis, during which banks in core European countries were 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 sovereign banks and stressed banks. An impaired banking sector has limited ability to support economic activity, which in turn further strains public finances, eventually putting in question the ability of the sovereign to clean up the banking system. The ECB (2011, 2012) identifies this adverse feedback loop as the key risk 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 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 much 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 in three major aspects. First, we further develop an econometric model which allows handling the high dimensionality in tail risk networks while producing sufficiently precise and robust quantities given the available data in rolling windows. Second, we employ a unique data set consisting of equity prices, CDS prices and quarterly balance sheet data of large European banks as well as CDS and government bond prices of corresponding sovereigns. This database allows us to cover a major fraction of the European banking and sovereign system. Third, we provide novel insights into time-varying tail risk dependencies and spillovers between European banks and sovereigns, particularly covering the 2008 global financial crisis and the subsequent European sovereign debt crisis. We show how network connectedness, fragmentation and interactions between European financial institutions and sovereigns change over this time period and how the state of the financial system is reflected in the topology of the underlying network.

Our empirical methodology builds on the framework proposed by (Hautsch, Schaumburg, and Schienle 2014a) (henceforth HSS2014) and (Hautsch, Schaumburg, and Schienle 2014b). 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), HSS2014 propose to use a statistical regularization and shrinkage method. The selection of individual-specific tail risk drivers gives a 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 HSS2014 from alternative methods for measuring and predicting systemic risk, see, e.g., Acharya, Pedersen, Philippon, and Richardson (2010), Adrian and Brunnermeier (2011), and Brownlees and Engle (2012).

In this paper, we further develop the methodology introduced by HSS2014 in two directions. First, we adapt the approach to make it feasible to use in situations, where the density of the network is high and the underlying sample period is relatively 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 of controlling 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. We therefore 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 of accounting for time-variations in companies' systemic riskiness and underlying network connections. Accounting for time variations via rolling window estimations, however, is crucial when the framework is used for surveillance and monitoring of the system building the basis for macroprudential regulation. To overcome this empirical difficulty and to address the tradeoff between estimation robustness on the one hand and capturing time-variability of the underlying relationships on the other hand, we propose combining 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. We show that this approach is empirically tractable and balances model flexibility and estimation robustness in the given context. Second, when estimating a company's systemic relevance, we explicitly account for the interconnectedness of an institution, measured by its network centrality. We empirically show that the latter is a significant factor of a firm's systemic risk contribution.

Empirically, we contribute to the literature in two major directions. First, focusing on 51 large European banks allows us covering 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 the banks and the 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.

Moreover, methodologically our paper is also related to earlier studies analysing contagion and co-movement in banks' equity prices using extreme value theory, in particular to Gropp, Duca, and Vesala (2009), who analyse cross-border contagion among European banks in 1994-2003 and to Bae, Karolyi, and Stulz (2003) and Hartmann, Straetmans, and De Vries (2004), who focus on cross-country spillovers. Finally, our paper is also closely related to the increasing literature analysing financial networks, contagion and systemic risk, see e.g. Allen and Gale (2000) and Cont, Moussa, and Santos (2013)[1].

The key findings are as follows: First, we observe that the density of the European financial network increases from 2006 onwards, peaks around the height of the financial crisis and significantly declines thereafter. Second, an interesting feature of the sovereign credit crisis 2011-2013 is a clear decline of banks' connectedness and an increasing market fragmentation reflected by a dominance of domestic (within-country) linkages. Third, the national fragmentation during the sovereign credit crisis is accompanied by increasing dependencies between sovereigns and financial firms, making particularly the CDS tail risk of Italy, Spain and Greece strongly dependent of the financial sector. Fourth, the

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

topology of the European banking and sovereign network clearly changes when moving from the 2008 financial crisis to the current credit risk crisis. We find that the state of the system is well reflected in underlying network statistics which might be used as (rough) indicators for monitoring purposes.

From a methodological point of view, we show the importance of explicitly linking a bank's or sovereign's connectedness (e.g., reflected by its network centrality) to its (time-varying) systemic risk contribution. Moreover, particularly relevant for the European sovereign debt crisis, we stress the relevance of sovereign risk as banks' tail risk driver. Finally, 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 need of addressing a dense tail risk network.

The remainder of the paper is organized as follows. Section 2 explains the estimation methodolgy 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 in estimating systemic risk contributions works in two steps. The first step is necessary for determining the time-varying topology of the underlying tail risk network of banks and sovereigns. While this 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 constitute generalized tail risk networks for the European bank-sovereign system by substantially adapting and extending the approach in Hautsch, Schaumburg, and Schienle (2014a). In particular, we account for potentially time-varying bank sovereign spillovers and explicitly include sovereigns as 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), $VaR_{q,t}^i$, given a set of i-specific risk drivers R_t^i, i.e.,

$$\Pr(-X_t^i \geq VaR_{q,t}^i | R_t^i) = q, \tag{1}$$

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 full set of tail risk drivers of a bank/sovereign i thus consists of loss exceedances of banks/sovereigns other than i, which we denote as 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 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

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

Thus, in theory, it appears straightforward to estimate this model by standard linear quantile regression techniques (see Koenker and Bassett (1978)). But in practice, this is infeasible. The challenge of this task is that 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.

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 approach. 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 de-meaned form of the set of *potential* 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 helps to identify *relevant* loss exceedances as those regressors with sufficiently large marginal effects. Correspondingly, a regressor is de-selected if its (adaptive) LASSO estimate in $\widetilde{\alpha}^i_2$ 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^i_k.

[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.

Both λ^i and w_k^i are chosen in a data-driven way, optimizing the score of (3) with remaining constants 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 along 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.

Moreover, to allow for time-variations in network dependencies, we perform this analysis based on rolling windows, where sample windows of 24 months are rolled over at a yearly frequency. 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. Thus, networks are year-specific and can vary on an annual basis. Correspondingly, the VaR of firm/sovereign i at time t in year t_0 is determined as

$$\widehat{VaR}_t^{i,t_0} = \widehat{\alpha}_0^{i,t_0} + \widehat{\alpha}_1^{i,t_0} Z_{t-1}^i + \widehat{\alpha}_2^{i,t_0} N_t^{(i,t_0)}, \tag{4}$$

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 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 HSS2014, we denote this effect as realized systemic risk beta. To quantify this measure, the system VaR VaR_t^s is taken as the VaR of a value-weighted portfolio of firms representing the financial system. Moreover, as explained in more detail below, we build groups $g = 1, \ldots, G$ of institutions, which allows us to estimate certain *group-specific* marginal effects 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

$$VaR_t^s = \beta_g^{t_0}(B_t^i, net_t^{i,t_0})\widehat{VaR}_t^{i,t_0} + \gamma^{i,t_0} + \theta_1^{t_0} Z_{t-1}^s + \theta_2^{t_0} R_t^{(i,t_0)} \ , \tag{5}$$

where the (time-varying) marginal effect β^{t_0} is referred to *systemic risk beta*. Apart from time variations of β^{t_0} arising from the rolling window estimation, we allow for additional variation *within* a two-year period (indexed by t_0) by modeling β^{t_0} as a function of firm-specific characteristics B_t^i and an i-specific local network measure, net_t^{i,t_0}, defined as the logarithm of one plus the out-degree of node i in the network topology.[3] The latter characterizes the firm's connectedness 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. 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 relevant for bank i in the first step, and Z^s contain macro-financial state variables. The inclusion of these i-specific control variables, in particular the individual fixed effect and the aggregated indicator for network spillover influences on beta $R^{(i,t_0)}$, provide a robust way to obtain unbiased estimates of β. To keep the approach computationally tractable, we assume β^{t_0} being linear in its components within a group $g \in \{1, \ldots, G\}$ 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 found as being similar in terms of their (average) marginal systemic impact and their marginal effects with respect to the variables B_t^i, allows estimating the parameters in (6) group-wise instead of individual-specific. In practice, we suggest a simple and straightforward data-driven procedure to obtain adequate groups, which we outline below in the empirical section. Thus, groups are objective and yield 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. Thus, the coefficients of control variables from the system Z^s and from the network $R^{(i,t_0)}$ are common across all institutions, while influences of balance sheet characteristics on the time-variation of β can vary across subgroups in estimates of $\delta_g^{t_0}$. 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 β^{t_0}. Moreover, we can estimate all coefficients of (5) and (6) in one step, in contrast to a multiple-equation estimation as in Hautsch, Schaumburg, and Schienle (2014b). 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

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

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

This is the measure according to which 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. Our rankings in the following are based on realized systemic risk betas.

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 51 banks in the sample is shown in Table 1. For each institution, we collect quarterly balance sheet data as well as daily equity prices covering the period from 01/07/2006 to 30/06/2013 from Bloomberg. If available, we also collect corresponding data on 5-year senior CDS spreads. Stock prices enter the regressions in the form of returns; CDS prices in first differences.

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. Loan loss reserves and return on assets represent asset quality, 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. We also collect the release date of the balance sheet information and merge it with the stock price data accordingly to use the data in real-time manner.

The dataset also includes macro-financial state variables. We use the Euribor-OIS spread as 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. 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 yields on 10-year benchmarks bonds, the slope of the yield curve as measured by the yield difference between 10-year and 2-year bonds as well as the 5-year sovereign CDS spreads. The Stoxx Europe 600 Financial Services index is used to represent the financial system in the second stage.

The macro-financial state variables listed above are also used as control variables Z_t^s in the second stage regression. Moreover, as variables driving the time variability of systemic risk betas, B_t^i contains the subset of balance sheet characteristics with a distinct macroprudential interpretation, in this case leverage and size as defined above. All economic and financial variables come from Bloomberg.

4 Results

4.1 Time-varying tail risk networks of banks

Figures 1 and 2 and Tables 2 and 3 visually and quantitatively characterize the evolution of tail dependence networks of all financial companies for all six (overlapping) two-year subperiods. Here, the external influences Z_t^i on the network 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 connectedness 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.

As Figures 1 and 2 show, 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 2.[4] 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.

[4] 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.

The colour of the nodes, which indicates 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 predominantly 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 2, 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 to the rest of the system.

Third, Table 3 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.

Fourth, 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 but also the French BNP Paribas, Credit Agricole and Societe Generale, as well as the Portuguese Espirito Santo Financial Group, the Belgian Dexia, Bank of Ireland, the Royal Bank of Scotland and 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 the most strongly interconnected, while in 2008-2010 this role is taken by 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, also Credit Agricole belongs to this group at the very beginning 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. In particular, CDS prices reflect investors' expectations on default risks, and thus are explicitly connected to extreme market movements. Moreover, utilizing CDS returns allows us constructing and analyzing a network of *both* financial companies and 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[5], 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 equity returns as underlying variables we utilize CDS returns of both banks *and* sovereigns. Accordingly, bank and sovereign CDS returns are both penalized in the weighted LASSO approach. As illustrated below, this leads to an overall higher 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). Conversely, in case 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 the increase of the sovereign debt crisis (2010-2012). Particularly, the CDS tail risk of France, Italy and Spain becomes deeply connected with the tail risk 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, where also Portugal, Ireland and Austria gain importance. The centrality of the German sovereign, on the other hand, is comparatively low, confirming Germany's role as anchor of stability as opposed to a transmitter of tail risk.

Table 4 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, where 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 crisis intensity. While the 2010-2012 period was just as critical to the survival of European Monetary Union as the 2008-2010 period, the first was not detected as problematic by pure bank networks.

The increase of sovereigns' connectedness is particularly true for countries which have been strongly affected by the sovereign debt crisis (so-called 'crisis countries'), i.e.,

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

Ireland, Italy, Portugal and Spain. According to Table 5, the connectedness of 'crisis countries' and 'non-crisis countries' is relatively similar during the global financial crisis (2006-2008).[6] In the subsequent periods, however, we observe a clear increase of the average centrality of 'crisis countries', while others are only affected to a much smaller extend. 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 6, reveals supportive information for 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, the picture strongly reverts with the share of sovereign-bank linkages of 'crisis countries' increasing, where that of the other countries remains at about the same level. Hence, it is not only the increasing interconnectedness of a sovereign, but obviously 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, companies within a group should be preferably similar in terms of their average marginal systemic impact and the way how characteristics B influence this effect. In this case, the coefficients of components of the systemic risk beta (6) are captured sufficiently well by respective *common* parameters within the group. On the other hand, we aim at keeping the number of groups small to ensure the availability of a sufficient number of observations per group and thus the precision of the resulting beta estimate. Investigating different combinations and number of groups we found a setting as follows the most appropriate: In particular, the regressions are based on three groups, where 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 as 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, the node sizes reflect the quartiles of the corresponding underlying (cross-sectional) distributions with banks being in the respective top quartile explicitly labeled.

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

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 tend to be 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 riskindex. Conversely, the Swedish banks display a comparatively strong correlation with the riskindex, but are very safe individually.

Table 8 ranks banks according to marginal systemic relevance and lists the associated group, as well as the bank's size, leverage and interconnectedness. Table 8 shows that the estimated systemic risk beta increases with size and leverage as captured by the grouping. The last column demonstrates that more interconnected banks likewise display a higher degree of tail dependence. Thus, size, leverage, and interconnectedness modify the estimated systemic risk beta in line with theoretical priors. More importantly, the results also suggest that traditional balance sheet characteristics alone provide an incomplete account of systemic relevance.

The third plot of Figure 5 shows the distribution of realized systemic risk, which integrates 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 of the other. Only three banks from what is typicially considered the euro area core were at the time present in the fourth quartile of the realized systemic risk distribution: Dexia, KBC, and Natixis. Perhaps more surprisingly, this applies to 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.

4.4 Robustness Checks

To validate our analysis, we conducted various robustness and sensitivity checks: First, we analyzed the sensitivity of results with respect to the choice of the riskindex $R^{(i,t_0)}$. While the form of weighting (e.g., equally weighting instead of value-weighting) does not qualitatively change the results, its role as control variable for a consistent estimation of systemic risk betas is distinct. Actually, leaving out $R^{(i,t_0)}$ influences the estimates of systemic risk betas and consequently the resulting systemic risk ranking. Second, we checked 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 additional control in the vector B. This extension, however, produces multi-collinearity effects inducing instable estimates. Therefore, a specification with leverage, size and net_t^i as the drivers of time variabilities of systemic risk betas turns out to be sufficient.

5 Conclusions

The paper provides a framework for estimating bank-specific time-varying systemic risk contributions 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 degree of price comovement with the left tail of the financial system return distribution, which we refer to as marginal systemic relevance. Unsurprisingly, we find that at the height of the sovereign debt crisis banks from programme countries exhibit the greatest degree of fragility. We also document that marginal systemic relevance increases with size, leverage, and interconnectedness. Banks from programme countries also rank highly in the distribution of realized systemic risk.

The systemic risk contributions are based on tail dependence networks that can be used as monitoring tool and thus are an output of interest in its own right. We show that network density varies as expected with the intensity of the financial crisis. We further document that the fragmentation of the European financial system is reflected in 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 sovereign and to explicitly represent bank-sovereign interaction. 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.

Appendix

Selection algorithm for relevant risk drivers

We adapt the data-driven procedure of Hautsch, Schaumburg, and Schienle (2014a) 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 reestimate the obtained model for obtaining unbiased coefficients (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 $R_{t_0-\tau}, \ldots, R_{t_0-\tau}$ denoted as $U_1, \ldots, U_\tau$. Conditional on observations of R, calculate the corresponding value of the random variable,

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

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

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

where $Q(\Lambda^{i,t_0}, 1-\alpha|R_{t_0}-)$ denotes the $(1-\alpha)$-quantile of Λ^{i,t_0} given $R_{t_0-\tau}, \ldots, R_{t_0-\tau}$ 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 equidistant grid.

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

$$\breve{\alpha}_q^{i,t_0} = \text{argmin}_{\alpha^i} \frac{1}{\tau} \sum_{t=1}^{\tau} \rho_q \left(X_{t_0-t}^i + \alpha^i R_{t_0-t} \right) . \tag{8}$$

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 equidistant 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,

$$\widetilde{\alpha}_q^{i,t_0} = \text{argmin}_{\alpha^i} \frac{1}{\tau} \sum_{t=1}^{\tau} \rho_q \left(X_{t_0-t}^i + \alpha^i R_{t_0-t} \right) + \lambda^{i,t_0}(c) \frac{\sqrt{q(1-q)}}{\tau} \sum_{k=1}^{K} w_k^{i,t_0} \hat{\sigma}_k |\alpha_k^i| \ , \tag{9}$$

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 (9) 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

Table 1: Banks in the sample

ID	Name	Country
alb	Allied Irish Banks	ie
alp	Alpha Bank	gr
crg	Banca Carige	it
bnp	BNP Paribas	fr
bmp	Monte dei Paschi	it
bpe	Bance Popolare dell'Emilia Romagna	it
pmi	Banca Popolare di Milano	it
bpi	Banco BPI	pt
bbv	BBVA	es
bcp	Banco Comercial Portugues	pt
bpi	Banco Popolare SC	it
pop	Banco Popular Espanol	es
san	Banco Santander	es
sab	Banco de Sabadell	es
boc	Bank of Cyprus	cy
bkt	Bankinter	es
bar	Barclays	gb
cbk	Commerzbank	de
aca	Credit Agricole	fr
ccf	Credit Industriel et Commerciale	fr
dan	Danske Bank	dk
dbk	Deutsche Bank	de
dpb	Deutsche Postbank	de
dex	Dexia	be
eur	EFG Eurobank	gr
ebs	Erste Group Bank	at
esf	Espirito Santo Financial Group	pt
bki	Bank of Ireland	ie
hsb	HSBC	gb
ing	ING	nl
ipm	Irish Life and Permanent	ie
isp	Intesa Sanpaolo	it
kbc	KBC	be
beb	Landesbank Berlin	de
llo	Lloyds	gb
cpb	Marfin	cy
ete	National Bank of Greece	gr
knf	Natixis	fr
nda	Nordea	se
otp	OTP Bank	hu
tpe	Piraeus	gr
poh	Pohjola	fi
pko	Powszechna Kasa	pl
rbs	Royal Bank of Scotland	gb
seb	SEB	se
gle	Societe Generale	fr
sta	Standard Chartered	gb
shb	Svenska Handelsbanken	se
swe	Swedbank	se
ucg	UniCredit	it
ubi	Unione di Banche Italiane	it

Table 2: Characteristics equity price networks

	(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 underlying networks do not penalize sovereign bond yields.

Table 3: Financial fragmentation

	(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 titled crisis 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.

Table 4: Characteristics CDS price networks

	(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 fragementation as represented by the share of domestic linkages, and sovereign bank interaction evolve over time. The underlying networks penalize sovereign cds return to the same extent as banks cds returns. The share of domestic linkages only takes into account connections between banks.

Table 5: Sovereign interconnectedness

	(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 titled crisis refers to the simple average for a group of countries composed of ES, IE, IT, and PT. Non-crisis refers to the average over all other countries in the sample.

Table 6: Sovereign-bank interaction

	(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 of a sovereign directed at banks. The column titled crisis refers to the simple average for a group of countries composed of ES, IE, IT, and PT. Non-crisis refers to the average over all other countries in the sample.

Figure 1: Time varying tail dependence networks

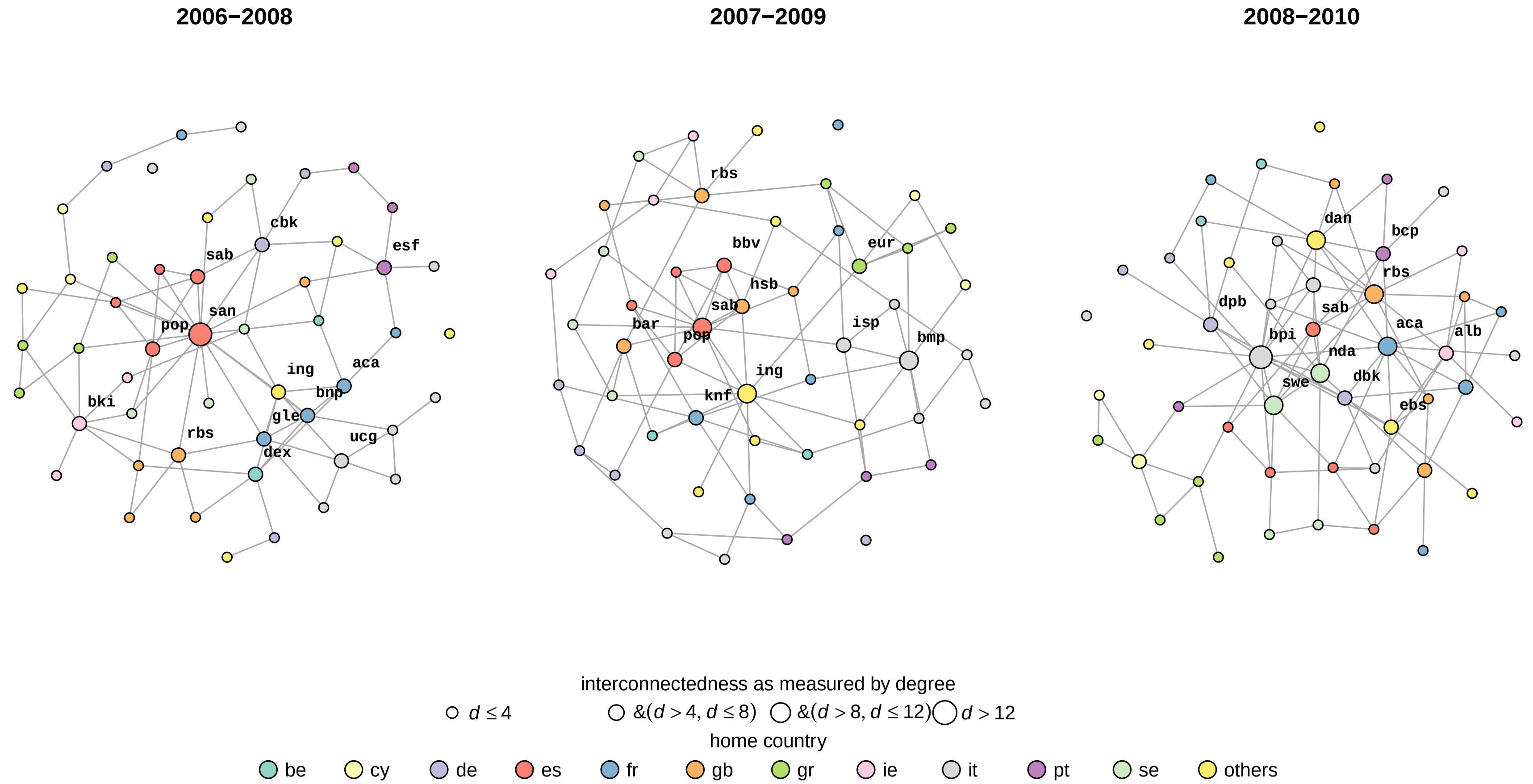

Figure 2: Time varying tail dependence networks

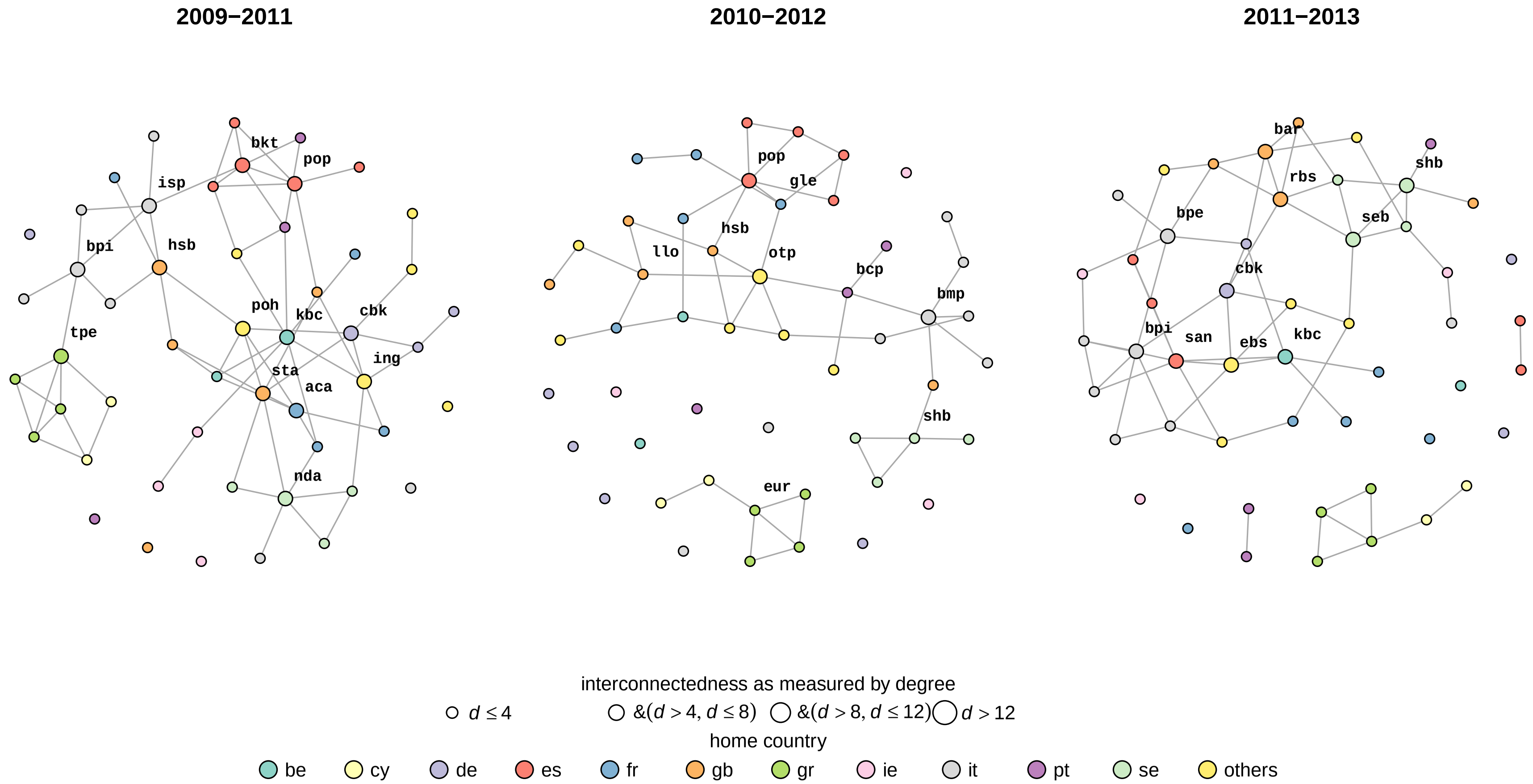

Figure 3: Sovereign bank interaction

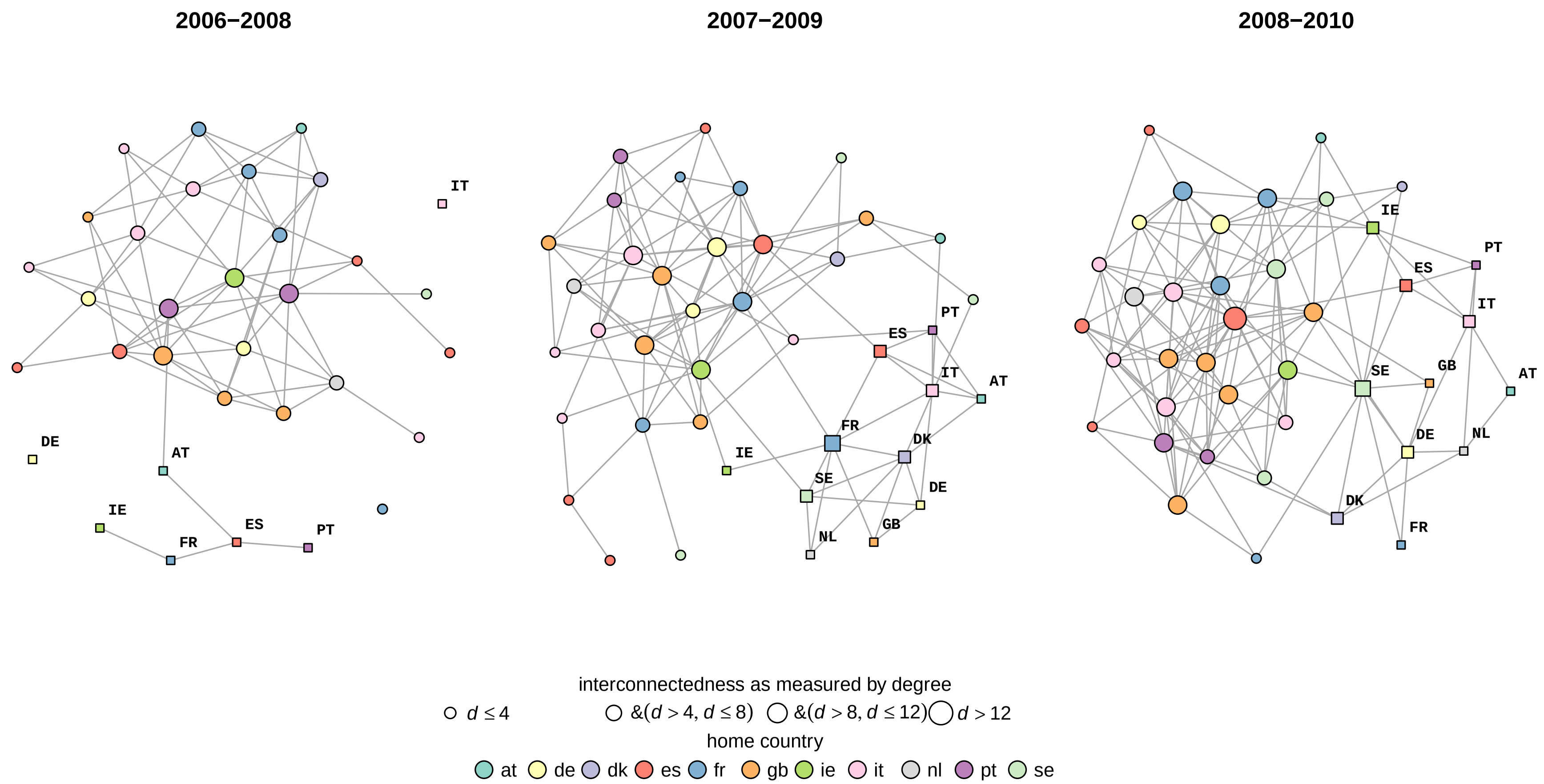

Figure 4: Sovereign bank interaction

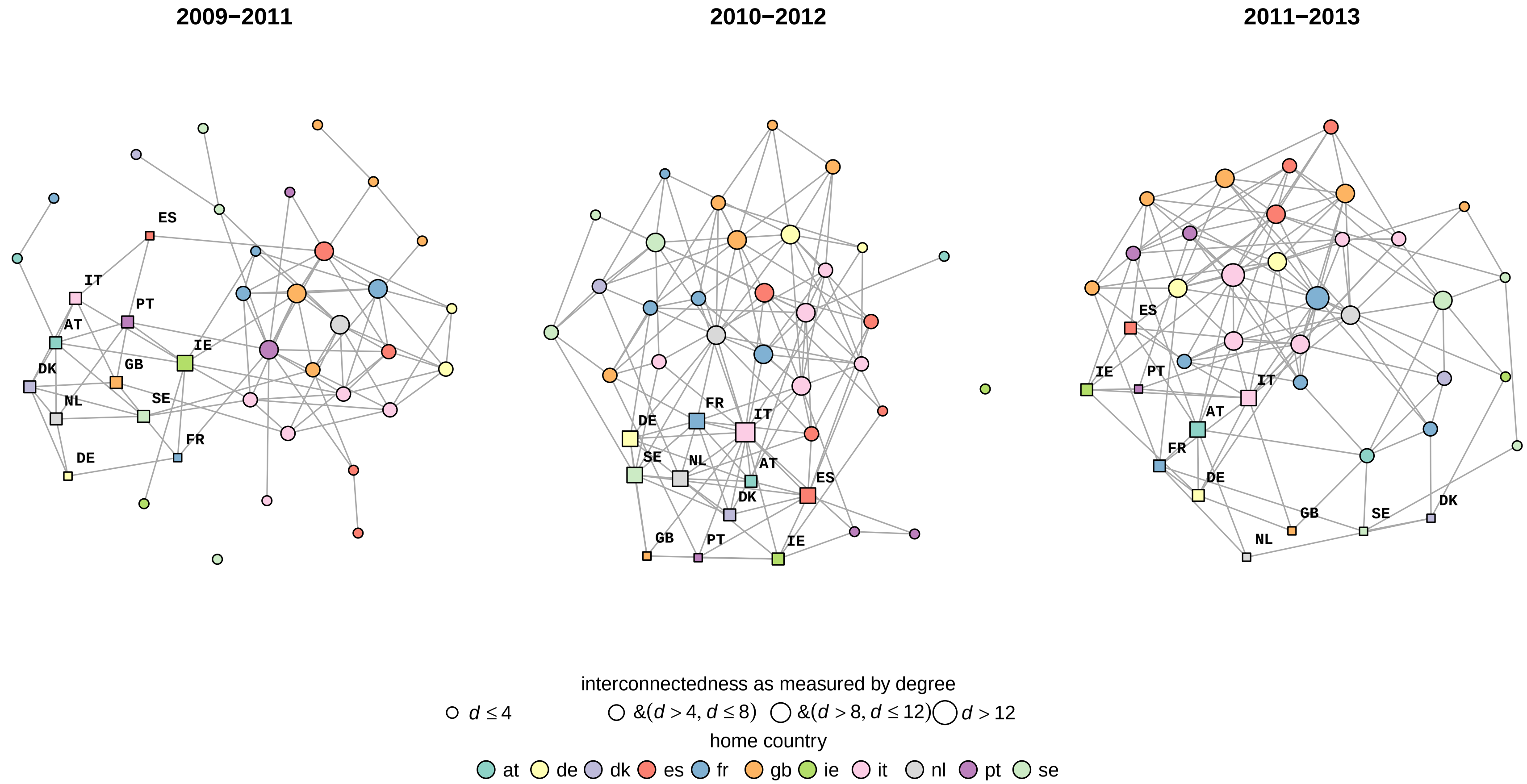

Figure 5: Systemic risk contributions June 2012

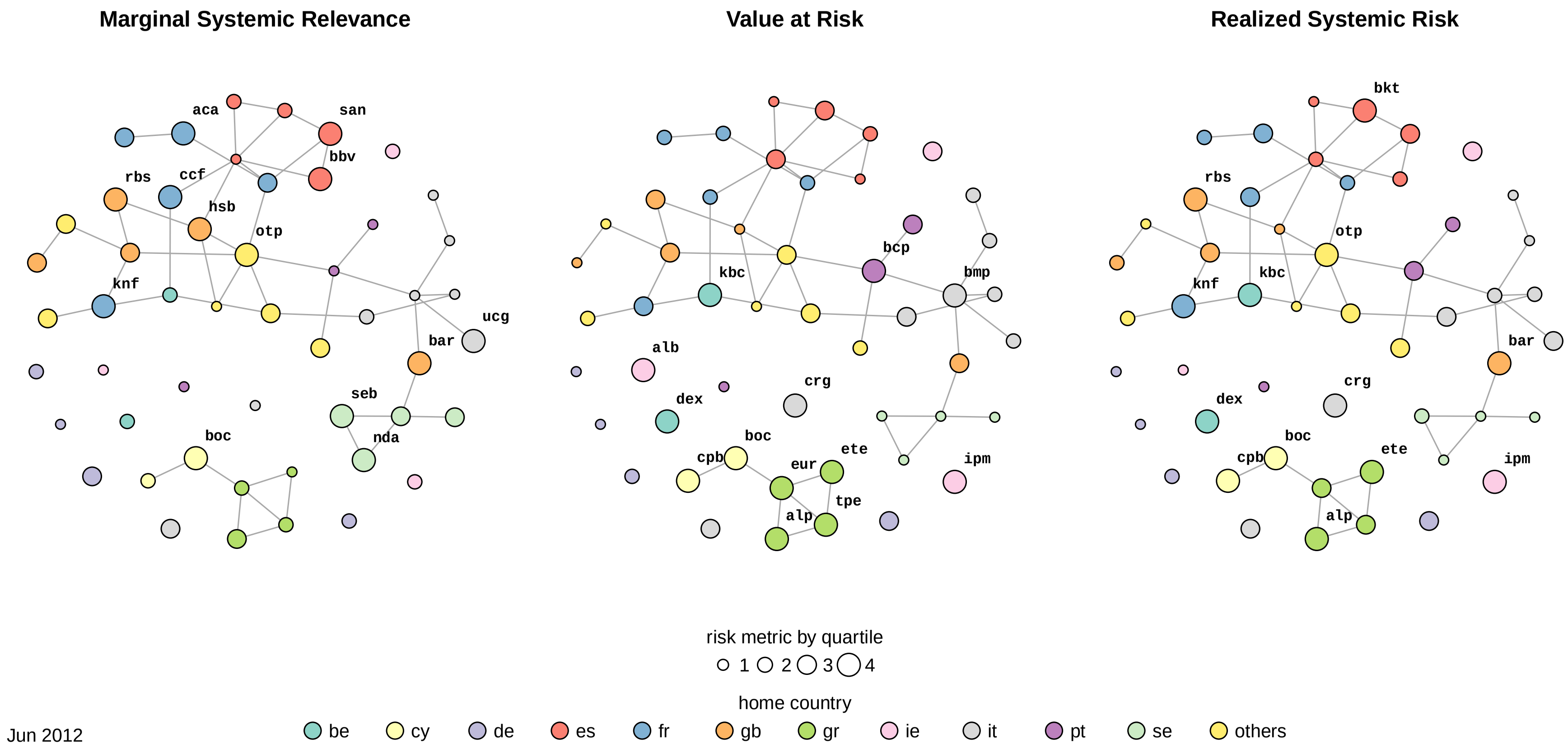

Table 7: Realized systemic risk: June 2012

Rank	Bank name	ID	Country	**Realized beta**	β	$V\hat{a}R$
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

Table 8: Systemic risk betas and driving components: June 2012

Bank name	β	group	Size	Leverage	Net
Banco Santander	0.2878	2	7.1572	16.8518	1.3863
HSBC	0.2850	2	7.5899	15.9292	1.0986
Natixis	0.2779	3	6.2299	26.1202	1.3863
Royal Bank of Scotland	0.2768	2	7.4282	19.0981	1.0986
BBVA	0.2729	3	6.3977	15.3705	1.0986
Barclays	0.2725	3	7.5333	29.0104	1.0986
OTP Bank	0.2679	1	3.5264	7.3755	1.7918
Credit Agricole	0.2657	3	7.4519	36.1905	1.0986
SEB	0.2595	3	5.5769	21.7143	1.0986
Credit Industriel et Commerciale	0.2553	3	5.4523	25.2925	1.0986
UniCredit	0.2522	2	6.8385	14.5713	0.6931
Nordea	0.2432	3	6.5425	25.9949	0.6931
Erste Group Bank	0.2388	3	5.3786	17.7028	0.6931
Standard Chartered	0.2383	2	6.1254	13.7613	0.6931
Danske Bank	0.2373	3	6.1540	28.4674	0.6931
Svenska Handelsbanken	0.2335	3	5.6288	26.9227	0.6931
Bank of Cyprus	0.2281	1	3.6547	15.1471	1.0986
Intesa Sanpaolo	0.2154	2	6.4810	12.4980	0.0000
Lloyds	0.2143	3	7.0558	21.4171	0.0000
Swedbank	0.2140	2	5.3662	19.1752	0.6931
BNP Paribas	0.2139	3	7.5834	28.0491	0.0000
ING	0.2112	3	7.1243	25.8275	0.0000
Alpha Bank	0.2108	1	4.0530	15.8155	1.0986
Societe Generale	0.2087	3	7.0850	28.3256	0.0000
Deutsche Bank	0.2065	3	7.6513	37.5956	0.0000
Dexia	0.2041	3	6.0229	21.4107	0.0000
Pohjola	0.1982	1	3.7527	17.0224	0.6931
Commerzbank	0.1962	3	6.5382	36.8333	0.0000
Bankinter	0.1865	2	4.1047	19.6879	0.6931
Deutsche Postbank	0.1852	3	5.3287	35.8836	0.0000
Banco de Sabadell	0.1807	1	4.6570	14.8263	1.0986
Bance Popolare dell'Emilia Romagna	0.1805	1	4.0969	16.1703	0.6931
Bank of Ireland	0.1760	2	5.0427	18.3763	0.0000
EFG Eurobank	0.1715	1	4.2985	2.1094	1.0986
Unione di Banche Italiane	0.1661	1	4.8791	12.7310	1.0986
Piraeus	0.1654	1	3.8606	3.3544	0.6931
Banco Popolare SC	0.1647	1	4.9048	12.6513	1.0986
Banco Popular Espanol	0.1635	1	5.0639	15.7241	1.0986
KBC	0.1598	2	5.6721	59.4140	0.6931
Marfin	0.1588	1	3.4617	15.3970	0.0000
National Bank of Greece	0.1553	1	4.6453	2.1094	1.0986
Banco BPI	0.1499	2	3.8012	39.6606	0.6931
Monte dei Paschi	0.1465	1	5.4412	15.9840	1.0986
Irish Life and Permanent	0.1441	2	4.2772	28.7822	0.0000
Banca Carige	0.1326	1	3.8607	11.6481	0.0000
Banca Popolare di Milano	0.1305	1	3.9705	13.1303	0.0000
Banco Comercial Portugues	0.1283	1	4.5221	24.7166	0.0000
Powszechna Kasa	0.1267	1	3.8250	7.9325	0.0000
Landesbank Berlin	0.1256	2	4.9002	49.8018	0.0000
Allied Irish Banks	0.0917	1	4.9174	15.7617	0.0000
Espirito Santo Financial Group	0.0842	2	4.4446	70.8370	0.0000

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