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Forecasting systemic impact in financial networks

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Abstract

We propose a methodology for forecasting the systemic impact of financial institutions in interconnected systems. Utilizing a five-year sample including the 2008/9 financial crisis, we demonstrate how the approach can be used for timely systemic risk monitoring of large European banks and insurance companies. We predict firms' systemic relevance as the marginal impact of individual downside risks on systemic distress. The so-called systemic risk betas account for a company's position within the network of financial interdependencies in addition to its balance sheet characteristics and its exposure towards general market conditions. Relying only on publicly available daily market data, we determine time-varying systemic risk networks, and forecast systemic relevance on a quarterly basis. Our empirical findings reveal time-varying risk channels and firms' specific roles as risk transmitters and/or risk recipients.

Keywords: Forecasting systemic risk contributions, time-varying systemic risk network, model selection with regularization in quantiles

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

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1. Introduction

The breakdown risk for the financial system induced by the distress of an individual firm has long been neglected in financial regulation. Up to the financial crisis 2007-2009, this systemic risk has been exclusively attributed to the idiosyncratic risk of an institution, abstracting from the strong network cross-dependencies in the financial sector causing potential risk spillover effects. In an extensive study for the U.S. financial system, however, Hautsch, Schaumburg, and Schienle (2012) (HSS) show that it is mainly the interconnectedness within the financial sector that determines the systemic relevance of a particular firm. To quantify the systemic impact of an individual company, they propose the so-called realized systemic risk beta, the total effect of a company's time-varying Value at Risk (VaR) on the VaR of the entire system. Firms' tail risk is determined from company-specific relevant factors among other companies' tail risks, individual balance sheet characteristics, and financial indicators, where components are selected as being "relevant" via a data-driven statistical regularization technique. The resulting individual-specific models give rise to a financial risk network, capturing exposures of financial firms towards the distress of others. These network risk spill-over channels contain important information for supervision authorities as sources for systemic risk. Their data-driven determination of firms' systemic relevance from publicly available data distinguishes HSS from the number of other recently proposed methods for refined measurement and prediction of systemic risk, see, e.g., Adrian and Brunnermeier (2011), White, Kim, and Manganelli (2010), Huang, Zhou, and Zhu (2009), Brownlees and Engle (2011), Acharya, Pedersen, Philippon, and Richardson (2010), Giesecke and Kim (2011), Billio, Getmansky, Lo, and Pelizzon (2012), Koopman, Lucas, and Schwaab (2011), Engle, Jondeau, and Rockinger (2012), or Schwaab, Koopman, and Lucas (2011) among many others.

Effective regulation requires models which can be used for forecasting and which are reliable even if estimation periods are short. The original HSS framework, however, is not tailored to short-term forecasting of systemic risk and must be adapted for prediction purposes. Firstly, the HSS-systemic risk network is static, i.e., it is estimated once using the entire dataset and then forms the basis for estimation of respective time-varying realized betas. However, empirical evidence suggests that network links might change over time, especially in crisis periods. Secondly, in order to exploit additional variation, quarterly balance sheet characteristics are interpolated by cubic splines over the analyzed time period. Therefore, out-of-sample forecasting is not possible. Thirdly, the penalty parameter required for the model selection step is chosen such that a backtest criterion is optimized. VaR backtests, however, generally rely on counting and analyzing VaR exceedances, which is reasonable when the time series is long. Though for short estimation periods, these tests should be replaced by more adequate quantile versions of F-tests.

In this paper, we extend the HSS framework to allow for flexible systemic risk forecasting. The estimation period is shortened using rolling windows of only one year of data. This excludes influence of back-dated events on current forecasts while still pertaining sufficient prediction accuracy. The models are re-estimated each quarter, resulting in time-varying systemic risk networks. Instead of interpolating, information on firm-specific balance sheets is only updated when it is published at the end of each quarter. The model selection penalty is chosen such that the in-sample fit in the respective annual observation window is optimal. This is examined via an F-test for quantile regression. The empirical analysis investigates systemic risk in Europe. The data set covers stock prices and balance sheets of major European banks and insurance companies as well as financial indicators, including country-specific variables, during the period around the 2008/9 financial crisis. We illustrate that our approach could serve as a monitoring tool for regulators as it captures and effectively predicts systemic relevance over time.

The remainder of the paper is structured as follows. Section 2 outlines the forecasting methodology and gives an algorithm for model selection and estimation of firm-specific VaRs. Furthermore, the estimation method for realized systemic risk betas is given. Section 3 describes the dataset, before discussing estimation results and their implications in detail in Section 3.2. Section 4 concludes.

2. Forecasting Methodology

We extend the framework of Hautsch, Schaumburg, and Schienle (2012) (HSS) and the HSS measure for systemic relevance in the presence of network effects, the realized systemic risk beta. Whereas HSS focus on a single *static* network as a basis for estimating systemic impact of financial institutions, we progress by determining *time-varying* networks in a forecasting setting. These allow capturing changing risk spillover channels within the system, which are tailored to short-term forecasts from the model.

2.1. Time-Varying Networks

In a densely interconnected financial system, the tail risk of an institution i at a time point t is determined not only by its own balance sheet characteristics Z^i_{t-1} and general market conditions M_{t-1} but also by indications for distress in closely related banks in the system. For each bank in the system, we count a corresponding return observation as marking a distress event whenever this return is below the empirical 10% quantile. In such cases, these extreme returns might induce cross-effects on the riskiness of other banks in the system. We record these as so-called loss exceedances, i.e., the values of returns in case of an exceedance of the 10% quantile and zeros otherwise. Accordingly, the set of potential risk drivers R for a bank i therefore comprises network impacts N^{-i}_t from any other bank in the system, where each component of N^{-i}_t consists of loss exceedances for any bank but firm i in the system.

We measure tail risk by the conditional Value at Risk, VaR^i, for firm i and by VaR^s for the system, respectively. Using a post-LASSO technique as in HSS, the large set of potential risk drivers $R_t = (Z^i_{t-1}, M_{t-1}, N^{-i}_t)$ for institution i can be reduced to a group of "relevant" risk drivers $R^{(i)}_t$. Selected tail-risk cross-effects from other banks in the system constitute network links from these banks to institution i. Repeating the analysis for all banks i in the system, relevant risk channels can be depicted and summarized in a respective network graph. The recent financial crisis, however, has shown that such network interconnections may change over time as the relevance of certain institutions for the risk of others might vary substantially. Thus adequate short-run predictions of systemic importance should mainly be based on *current* dependency structures. We address this issue by a time-dependent selection of relevant risk drivers $R_t^{(i,t)}$ according to the algorithm described below. Driven by the quarterly publication frequency of companies' balance sheet information we re-evaluate the relevance of all potential risk drivers for each institution in the system at the beginning of each quarter based on data from the respective previous year and incorporate the latest balance sheet news. We therefore obtain quarterly time-varying tail risk networks which reflect the most current information of risk channels within the financial system. They are tailored for short-term quarterly predictions of the systemic riskiness of firms in the system.

With the relevant risk drivers $R^{(i,t)}$ for firm i and time t in a specific quarter, individual tail risk can be determined from observations up to one year before t as

$$\widehat{VaR}_t^i = \widehat{\xi}_0^{i,t} + \widehat{\xi}^{i,t} R_t^{(i,t)} , \tag{1}$$

where coefficients $\widehat{\xi}$ are obtained in the post-LASSO step from quantile regression of X^i on $(1, R^{(i,t)})$ as part of the procedure described below.

Algorithm for selecting relevant risk drivers and determining their effects in firms' tail risk

We adapt the data-driven procedure of HSS to account for time-variation in tail risk networks and marginal systemic risk contributions. The automatic selection procedure is based on a sequential F-test in contrast to the backtest criterion in HSS. Determination of relevant risk drivers $R^{(i,t_0)}$ at the beginning of a quarter t_0 uses information of observations within the previous year. Hence it is based on approximately $\tau = 250$ observations $R_{t_0-\tau}, \ldots, R_{t_0}$, where each R_t consists of centered observations of the potential regressors and has K dimensions. We fix a ν-equidistant grid $\Delta_c = \{c_1 > \ldots > c_l =$

$c_1 - \nu(l-1) > c_L = 0\}$ for values of a constant c, where c_1 is chosen such that the corresponding penalty parameter is sufficiently large for selecting not more than one regressor into the model. For our purposes, we set $c_1 = 30$ and $\nu = 1$.

Step 1: For each $c \in \Delta_c$, determine the penalty parameter $\lambda^i_{t_0}(c)$ from the data in the following two sub-steps as in Belloni and Chernozhukov (2011):

Step a) Take $\tau + 1$ iid draws from $\mathcal{U}[0,1]$ independent of $R_{t_0-\tau}, \ldots, R_{t_0}$ denoted as $U_0, \ldots, U_\tau$. Conditional on observations of R, calculate

$$\Lambda^i_{t_0} = (\tau+1) \max_{1 \leq k \leq K} \frac{1}{\tau+1} \left| \sum_{t=0}^{\tau} \frac{R_{t_0-t,k}(q - I(U_t \leq q))}{\hat{\sigma}_k \sqrt{q(1-q)}} \right| .$$

Step b) Repeat step a) B=500 times generating the empirical distribution of $\Lambda^i_{t_0}$ conditional on R through $\Lambda^i_{t_0 1}, \ldots, \Lambda^i_{t_0 B}$. For a confidence level $\alpha = 0.1$ in the selection, set

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

where $Q(\Lambda^i_{t_0}, 1-\alpha|R_{t_0-t})$ denotes the $(1-\alpha)$-quantile of $\Lambda^i_{t_0}$ given R_{t_0-t}.

Step 2: Run separate l_1-penalized quantile regressions for $\lambda^i_{t_0}(c_1)$ and $\lambda^i_{t_0}(c_2)$ from step 1 and obtain

$$\widetilde{\xi}^{it_0}_q(c) = \text{argmin}_{\xi^i} \frac{1}{\tau+1} \sum_{t=0}^{\tau} \rho_q \left(X^i_{t_0-t} + R'_{t_0-t}\xi^i \right) + \lambda^i_{t_0}(c) \frac{\sqrt{q(1-q)}}{\tau} \sum_{k=1}^{K} \hat{\sigma}_k |\xi^i_k| \,, \quad (2)$$

with the set of potentially relevant regressors $R_{t_0-t} = (R_{t_0-t,k})^K_{k=1}$, componentwise variation $\hat{\sigma}^2_k = \frac{1}{\tau+1} \sum_{t=0}^{\tau} (R_{t_0-t,k})^2$ and 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 components in R with absolute marginal effects $|\widetilde{\xi}^i_{t_0}(c)|$ below a threshold $\tau = 0.0001$ keeping only the $K^{it_0}(c)$ remaining relevant regressors $R^{(i,t_0)}(c)$ for $c \in \{c_1, c_2\}$. As $c_1 > c_2$, the sets of selected relevant regressors are nested $R^{(i,t_0)}(c_1) \subseteq R^{(i,t_0)}(c_2) = \{R^{(i,t_0)}(c_1), R^{(i,t_0)}(c_2 \backslash c_1)\}$. If $R^{(i,t_0)}(c_2 \backslash c_1)$ is the empty set, restart Step 2 with $\lambda^i(c_2)$ and $\lambda^i(c_3)$ from Step 1. Otherwise re-estimate (2) without penalty term for the larger model c_2 only with the respective selected relevant uncentered regressors $R^{(i,t_0)}(c_2)$ and an intercept. This regression yields the post-LASSO estimates $\widehat{\xi_q^{it_0}}(c_2)$. Apply an F-test for joint significance of regressors $R^{(i,t_0)}(c_2\backslash c_1)$ at 5% level. If they are significant, restart Step 2 with $\lambda^i(c_2)$ and $\lambda^i(c_3)$ from Step 1b. Continue until additional regressors $R^{(i,t_0)}(c_{l+1}\backslash c_l)$ from penalty c_l to c_{l+1} are no longer found to be significant. Then the final model is obtained from c_l yielding the set of relevant regressors $R^{(i,t_0)}(c_2)$ with corresponding post-LASSO estimates $\widehat{\xi_q^{it_0}}(c_l)$ for the coefficients.

2.2. Forecasting Systemic Impact

In an interconnected financial system, we measure the systemic impact of a specific bank i as the total realized effect of its riskiness on distress of the entire financial system given network and market externalities. This can be empirically determined via

$$VaR_t^s = \alpha^{s,t} + \beta^{s|i,t}(Z_{t-1}^{i*})\widehat{VaR}_t^i + \gamma^{s,t}M_{t-1} + \theta^{s,t}\widehat{VaR}_t^{(-i,t)}\ , \tag{3}$$

where $\widehat{VaR}^{(-i)}$ comprises tail risks of all other banks in the system selected as relevant risk drivers for bank i in the corresponding network topology. The marginal effect $\beta^{s|i,t}$ of the risk of company i might vary linearly over time in selected firm-specific balance sheet characteristics Z_{t-1}^{i*}. Coefficients in (3) can be obtained via standard quantile regression analogously to (2) without penalty term. Corresponding to the one-year estimation window for the time-varying network, we also determine parameters in (3) at the beginning of each quarter, based on observations dating back no longer than one year. The systemic relevance of a company can then be predicted from the beginning of a quarter t_0 to the next quarter $t_0 + \tilde{\tau}$ as realized beta

$$\widetilde{\beta}_{t_0+\tilde{\tau}|t_0-}^{s|i} = \widehat{\beta}^{s|i,t_0}(Z_{t_0-1}^{i*})\widehat{VaR}_{t_0}^i \tag{4}$$

where $t-$ denotes information up to time t. Within a quarter, predictions are updated by

$$\widetilde{\beta}^{s|i}_{t+1|t-} = \widehat{\beta}^{s|i,t_0}(Z^{i*}_{t_0-1})\widehat{VaR}^i_t \tag{5}$$

for any time point $t_0 \leq t \leq t + \tilde{\tau}$.

3. Data and Results

3.1. Data

Our sample of financial firms comprises 20 European banks and insurance companies. A list can be found in Table 1. The dataset covers Europe-based banks deemed as systemically relevant by Financial Stability Board (2011), for which complete data sets over the considered period are available.[1] It includes the ten largest European banks by assets in 2010. Furthermore, six insurance companies are selected, all belonging (by assets) to the top 10 insurers in the world in 2010. The regressors explaining the individual Value at Risk (VaR^i) are selected among other companies' loss exceedances, individual balance sheet ratios, and several financial indicators, including country-specific variables.

From quarterly balance sheets obtained from Datastream/Worldscope, three key ratios are calculated: Leverage, correponding to total assets divided by total equity; maturity mismatch, the quotient of short-term debt and total debt; and size, defined as the logarithm of total assets. Furthermore, we include quarterly stock price volatility in the set of possible regressors, which is estimated over the time span between quarterly reports. Instead of interpolating the data to daily values, we keep them constant until new information is published.[2]

[1] Banco Espirito Santo is the only bank which is not listed by the Financial Stability Board. We include it because otherwise, financial firms from Southern Europe would be underrepresented.

[2] For simplicity, we assume that quarterly balance sheets become public information on fixed dates: March 31, June 30, September 30 and December 31.

The set of financial indicator variables contains the return on EuroStoxx 600, relative changes of the volatility index VStoxx, and returns on three major bond indices for Europe: IBOXX Sovereign, containing government bonds, iBOXX Subsovereigns, consisting of bonds issued by government owned banks, supranationals and other subsovereigns, and iBOXX Corporates. Furthermore, we include changes in three months Euribor, the interbank lending interest rate, and a liquidity spread between three months Eurepo, the average repo rate reflecting the cost of repurchase agreements, and the three month Bubill (German government bond rate) as proxy for the risk free rate. To capture aggregate credit quality in Europe, we also add the change in the one year and five year default probability indices from Fitch as well as the change in the five year continued series of the credit default swap index iTraxx Europe. Another two relevant economic indicators are the gold price and relative changes of the MSCI Europe Real Estate Price Index.

As proxies for the market's expectations on economic growth and to capture country-specific effects on individual VaRs, we include several ten year government bond yields (Germany, United Kingdom, Spain, United States, and Greece) as well as yield spreads (ten years minus three months yields) of German and U.S. government bonds. Finally, accounting for the global interconnectedness of financial markets, we include returns on financial sector indices, FTSE Financials Japan, Asia, and US.

When estimating systemic risk betas in the second stage, a subset of the above macro financial indicators is required as control variables. Here, we take the changes in the EuroStoxx 600 index, VStoxx, Euribor, iTraXX, the three FTSE Financial indices, the real estate index, and the spread between Eurepo and the Bubill rate.

3.2. Results

Time-varying tail risk networks

Having identified the tail risk drivers for each firm allows us constructing a tail risk network. Following HSS, we take all firms as nodes in a network and identify a network link from firm i to firm j whenever the loss exceedance of i is selected as a tail risk driver for j. Figures 1 to 3 show the resulting systemic risk networks for the 20 financial institutions computed based on one-year rolling windows from 2006 to 2010. In order to illustrate cross-country and inter-country risk channels, we order the institutions in the graph according to their (main) home countries.

We identify several risk connections which are quite stable over time and seem to be fundamental risk channels of the European financial network during the period under consideration. An interesting tail risk connection is the link between Royal Bank of Scotland (RBS) and Barclays. RBS was strongly affected by the break-down of the U.S. housing and credit markets and realized substantial write-downs in April 2008. In the beginning of 2009, RBS faced a record loss and was bailed out by the UK government which increased its stake in the company to 70 percent. Conversely, Barclays was relatively well funded until beginning of 2008 and even explored options to take over the defaulting U.S. investment bank Lehman Brothers. A further bolstering of Barclays' balance sheet was due to the raise of new capital by investors in fall 2008. Consequently, Barclays was less exposed to credit crunches and did not participate in government's insurance schemes for toxic assets. The network analysis, however, reveals that both banks have been deeply connected. Being bi-directional before the crisis, the links became particularly pronounced and rather one-directional during the financial crisis. In particular, RBS received substantial tail risk from Barclays further increasing RBS's potential losses and making both companies systemically risky. Interestingly, the strong risk connection between Barclays and RBS vanishes in the aftermath of the financial crisis which might be a result of RBS's bailout and ongoing re-structuring in both banks. Persistent risk connections are also identified between Deutsche Bank and various big insurance companies, particularly Allianz as well as between Deutsche Bank and Commerzbank. The latter faced significant distress due to investments in toxic assets originating from the U.S. housing market, and was the first commercial lender in Germany accepting capital injections from the government. In the beginning of 2009, Commerzbank was partly nationalised with the government taking a 25% stake. Our analysis reflects that the distress of Commerzbank also spilled over to Deutsche Bank and thus in turn to big insurances such as Allianz and Münchener Rück. Hence, governmental support of Commerzbank was an important step to reduce its systemic risk contribution. This is empirically confirmed by our analysis as we observe a declining tail risk connectedness of Commerzbank after the bailout.

Furthermore, the networks reveal persistent connections between UBS and Credit Suisse, UBS and Crédit Agricole, Agricole and Société Générale as well as Credit Suisse and Agricole. The strong interconnections between these Swiss and French banks are likely to be driven by exposure to the same toxic assets and resulting liquidity shortages stemming from the U.S. market making these banks facing common funding problems. This happened during 2008/09, where all of these banks also received substantial tail risk spillovers from others. For instance, our analysis reveals that Credit Suisse was subject to tail risk inflow from Barclays and BNP Paribas which - according to the identified network connections - spilled over to the 'risk neighbors' of Credit Suisse. All of these banks received bailout packages from the Swiss and French government, respectively. As a possible consequence of these bailouts and a relaxation of the bank's funding situation in the aftermath, Credit Suisse's sensitivity to tail risk inflow from Barclays and BNP Paribas actually declined in 2009. Likewise, also the Spanish bank Santander and the Portugese bank Banco Espirito Santo seem to be deeply interconnected. As discussed below, Santander serves as an originator and transmitter of systemic risk to various other companies. These dependencies become particularly visible and pronounced during and after the financial crisis and might have contributed to the instability and distress of the Spanish banking system in 2012. Hence, though all these institutions operate on a global level, we still observe a substantial extent of persistent country-specific risk channels. These effects reflect a strong interconnectedness and consequently inherent instability of national banking systems. These within-country dependencies are complemented by cross-country linkages and industry-specific channels. Examples for the latter are tail risk connections prevailing within the insurance sector including Allianz, AXA, Aviva, Münchener Rück and Aegon. Their interconnectedness even increased during the financial crisis causing a substantial threat for the system in case of the default of one of these companies.

Our approach, however, also captures interesting time variations in tail risk channels. In particular, in 2008/09, we observe high fluctuations of network connections. Several risk channels identified in this period seem to be rather caused by crisis-specific turbulences and consequently vanished in the aftermath. Examples are connections from Santander to HSBC, BNP Paribas, Allianz and AXA. These links make Santander systemically quite risky as the bank obviously produced and transmitted tail risk to various major players in the system. These findings are confirmed by the estimated systemic risk betas shown below. A further example is a strong connection between ING and Aviva which built up and increased through the crisis and vanished thereafter. The Dutch bank ING realized significant losses, had to cut jobs in 2009 and received capital injections from the Dutch government. Hence, our analysis shows that substantial tail risk from ING was spreading out to Aviva and in turn to other insurances.

Analyzing the pure number of outgoing tail risk connections (illustrated by the size of nodes in the network graphs), we identify Barclays, Santander, AXA, BNP Paribas, ING, Société Générale and Crédit Agricole as deeply connected companies. Actually, the latter four were companies which have been bailed out by their governments and got partly nationalized. Our analysis indicates that these governmental capital injections were indeed justifiable as these companies have been (and still are) in the core of the network and therefore serve as distributors and multipliers of systemic risk. According to the identified network connections, failure of one of these institutions would substantially threaten the stability of the financial system.

Systemic risk rankings

Table 2 reports systemic risk rankings for all quarters between the beginning of 2007 and the end of 2010. They are based on realized systemic risk betas at the end of the respective foregoing quarter, and therefore contain forecasts of relative systemic relevance. Prior to the estimation, we conducted a test on joint significance of VaR^i and $VaR^i \cdot Z^{i*}$ with $i = 1, ...20$, for VaR^s, using all five years of data. Apart from two exceptions, all individual VaRs turn out to be statistically significant for the system's VaR. The two exceptions are, on the one hand, Banco Espirito Santo, which is the largest bank in Portugal, but much less internationally active than the other banks in our sample. On the other hand, Société Generale is found to be insignificant. We attribute this finding to the fact that in 2008, the bank was affected by large losses induced by the unauthorized propriety trading of one of its employees. This was a materialization of (idiosyncratic) operational risk, and may have distorted the test results concerning systemic relevance. We expect that on a longer horizon, Société Generale' systemic risk beta would be significant. In the following, however, we exclude it from the systemic risk rankings, together with Banco Espirito Santo.

It should be noted, that often differences in beta estimates between direct neighboring firms in the obtained rankings are small and thus not statistically significant. Hence orderings in Table 2 should rather be seen as an indication for a company's relative systemic importance characterizing groups of similar relative systemic impact.[3] Figure 5 illustrates the time-varying cross-sectional distribution of the estimated betas. We observe the overall highest systemic risk betas during the height of the financial crisis. Furthermore, representatively for other firms, we depict the estimated systemic impacts of Barclays, Crédit Agricole, Santander and UBS. It turns out that the respective systemic risk betas move in locksteps before mid 2008, but strongly diverge during the crisis. Similar relationships are also shown for other companies and reflect distinct crisis-specific effects.

[3] At some time points, estimated systemic risk betas become negative. We interpret this finding as negligible systemic impacts of the respective firm in the respective quarter and therefore omit it in the ranking.

These effects are supported by Table 2 revealing strong variations of the relative systemic riskiness during the crisis. This is obviously induced by a severe instability of the financial system during this period and is also confirmed by the high variability of network connections as discussed above. Conversely, a higher stability of systemic risk patterns over time is observed in the periods before and after the financial crisis (i.e., 2007 and 2010).

Overall, we identify BNP Paribas, HSBC and Santander as being most risky with the highest realized risk betas between 2007 and 2010. BNP Paribas was strongly affected by the credit crunch and an evaporation of liquidity in the funding market in 2007/08 and was bailed out by the French government end of October. Our findings reflect that after the bailout, BNP's systemic riskiness was still comparably high. According to the network analysis above, this is obviously due its strong interconnectedness making BNP to one of the major originators of tail risk spillovers in 2010. In contrast HSBC's connectedness is only moderate. However, its size and the identified tail risk connections to Barclays, BNP and Santander make it systemically quite risky. These connections became obviously quite relevant due to HSBC's heavy exposure to U.S. housing and credit markets. Consequently, the bank's distress induced by significant losses during the crisis have been spread out in the system resulting in a particularly high systemic riskiness around beginning of 2009. This is backed by the fact that HSBC had to cut a substantial amount of jobs at beginning of 2009. Our results indicate that also in the aftermath of the crisis, HSBC still remains systemically quite risky. In case of Santander, the relative systemic riskiness (compared to other banks) even tends to increase after the financial crisis (particularly in 2010). This finding might already indicate funding problems in the Spanish banking market becoming particularly evident in 2012. These results are in line with the findings of the network analysis above identifying Santander as a deeply interconnected bank being linked to several insurance companies and (particularly during the crisis) to other major players like Barclays and HSBC.

Monitoring systemic risk rankings over the course of the financial crisis provides interesting insights into the systemic importance of individual firms under extreme conditions of market distress. Four prominent examples are RBS, Barclays, Deutsche Bank and HBSC. According to the estimated systemic risk betas, we classify RBS as belonging to the most systemically risky companies in 2008. Also Barclays is identified as being systemically very relevant in several (though not all) periods in 2008/09. The identified network connections revealed that the strong connection between Barclays and RBS was obviously one driving force of the systemic relevance of both. This is also confirmed by the fact that the systemic relevance of both (as indicated by the realized betas) declined as the tail risk connection between both vanishes in 2009. Likewise, Deutsche Bank faces a steady increase of its systemic relevance in 2007 and belongs to the group of systemically most risky companies in 2008. This is confirmed by the network analysis above showing that particularly during 2008, Deutsche Bank was deeply interconnected with risk channels to various major insurance companies. Consequently, a default of Deutsche Bank would have had dramatic consequences for the insurance industry and thus the stability of the entire system. Although Deutsche Bank was not subject to any government bailouts it went through a process of substantial internal restructuring. This is confirmed by our estimates showing a decline of Deutsche Bank's systemic importance during 2009 and 2010.

Finally, for the post-crisis period, we observe a tendency for the insurance companies becoming relatively more risky. Particularly in 2010, Allianz, Aviva, Axa, Generali and Münchener Rück reveal relatively high (though not always significant) systemic risk betas. Likewise, also Société Générale and Credit Suisse are identified as systemically risky in 2010. These findings are confirmed by the network analysis showing a comparably high connectedness of Société Générale, Axa and Generali.

4. Conclusion

In this paper, we propose a framework for forecasting financial institutions' marginal contribution to systemic risk based on their interconnectedness in terms of extreme downside risks. There are four major challenges in this context: Firms' (conditional) tail risks are unobserved and must be estimated from data. Determining such individual risk levels appropriately results in high-dimensional models due to the large number of potential network connections. These network dependencies, however, are inherently instable over time. Therefore forecasting stability and responsiveness require careful balancing. To tackle these issues, we adapt the two-stage quantile regression approach by Hautsch, Schaumburg, and Schienle (2012) to a rolling window out-of-sample prediction setting based on time-varying networks.

In a sample of large European banks covering the period 2007 to 2010, the adapted procedure reveals the dynamic nature of interconnectedness and corresponding risk channels in the European financial system around and during the financial crisis. The time evolution of network dependencies provides valuable insights into a bank's role in the system identifying originators and transmitters of tail risk over time. Determined relevant tail risk connections and systemic risk rankings both provide valuable input for regulation. Given the need for better and more timely market surveillance, our approach can thus serve as a useful vehicle for providing a continuous assessment of systemic risk dependencies based on market data.

Appendix

Table 1: List of included financial institutions. As most of them provide a broad range of services, we differentiate between banks and insurance companies, according to their main field of business activities. Furthermore, we state the country their headquarters are located in.

Aegon (Insurance, NL)	Deutsche Bank (Bank, DE)
Allianz (Insurance, DE)	Generali (Insurance, IT)
Aviva (Insurance, UK)	HSBC (Bank, UK)
AXA (Insurance, FR)	ING Groep (Bank, NL)
Banco Espirito Santo (Bank, PT)	Lloyds Banking Group (UK)
Barclays (Bank, UK)	Muenchener Rueck (Insurance, DE)
BNP Paribas (Bank, FR)	Royal Bank of Scotland (Bank, UK)
Commerzbank (Insurance, DE)	Santander (Bank, ES)
Crédit Agricole (Bank, FR)	Société Générale (Bank, FR)
Credit Suisse (Bank, CH)	UBS (Bank, CH)

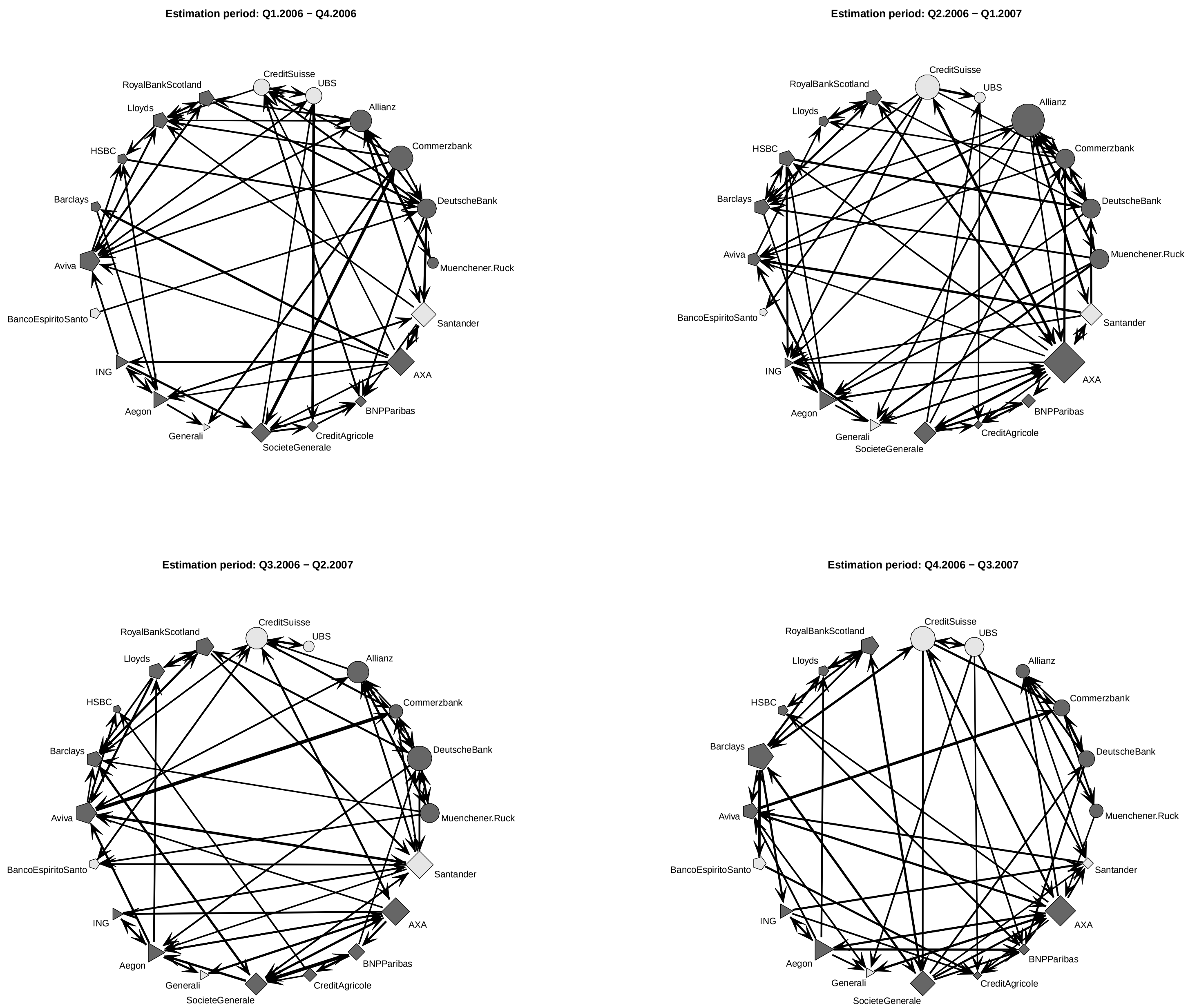

Figure 1: Estimates of yearly systemic risk network rolled over from Q4/2006 to Q3/2007.

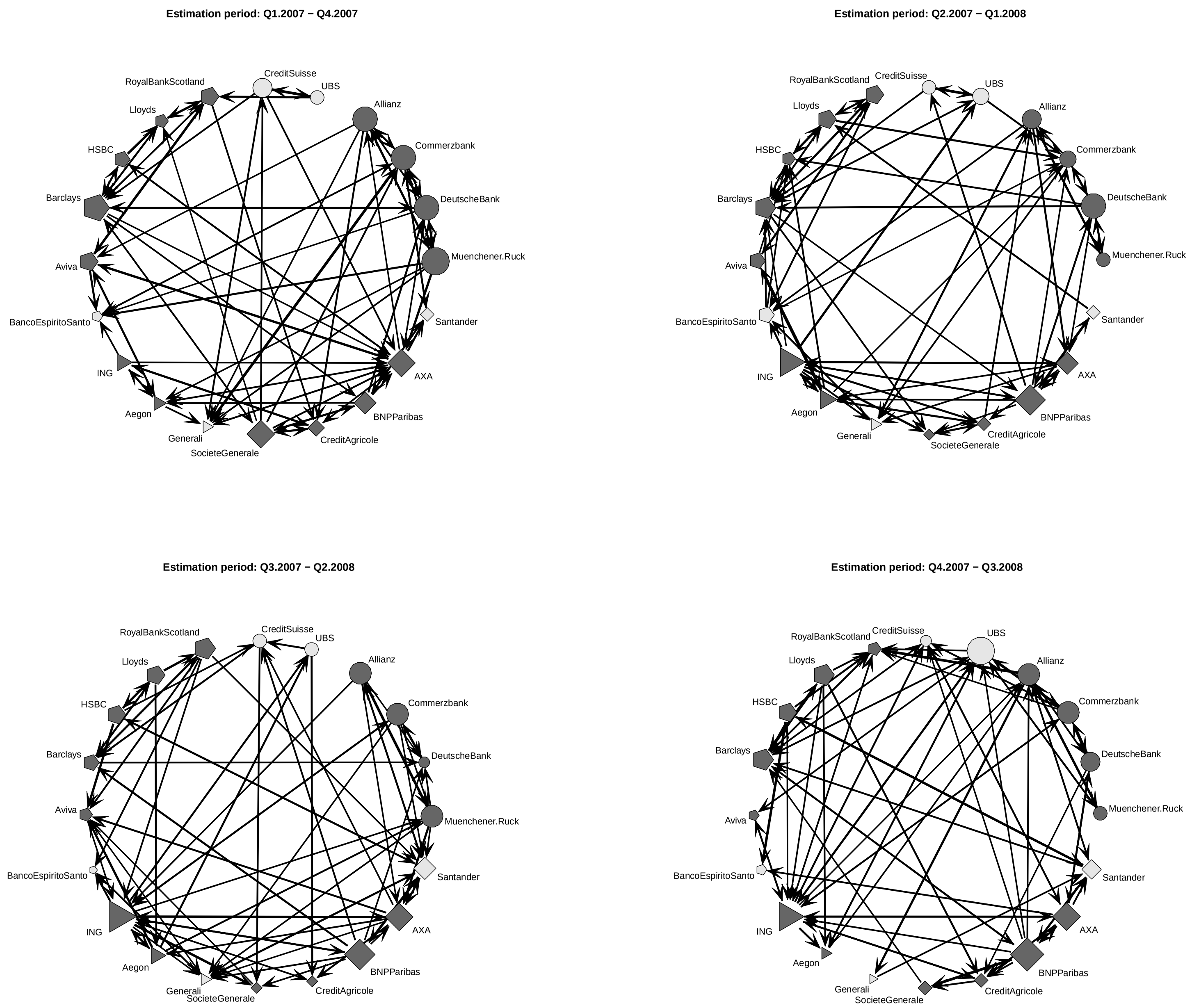

Figure 2: Estimates of yearly systemic risk network rolled over from Q4/2007 to Q3/2008.

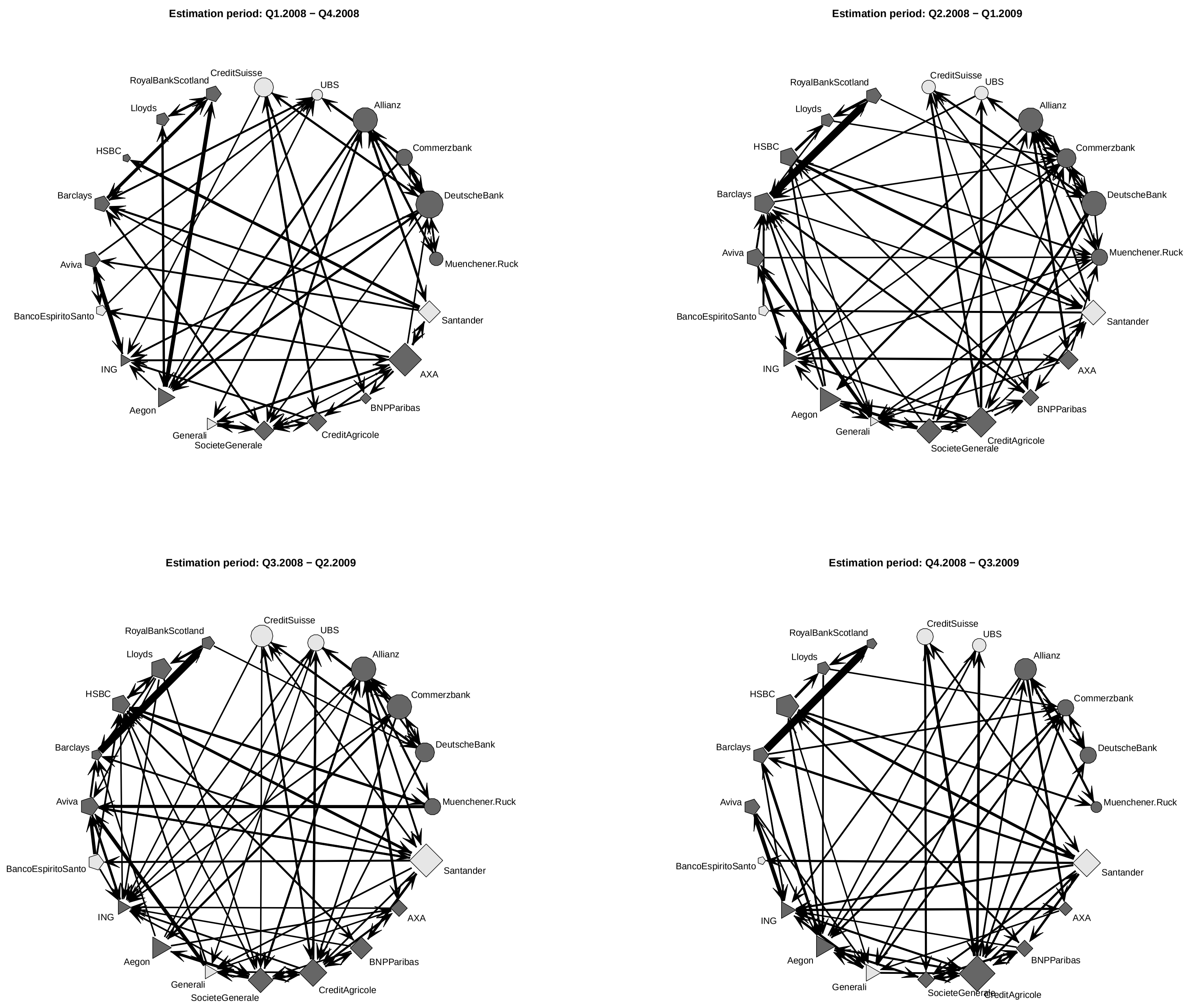

Figure 3: Estimates of yearly systemic risk network rolled over from Q4/2008 to Q3/2009.

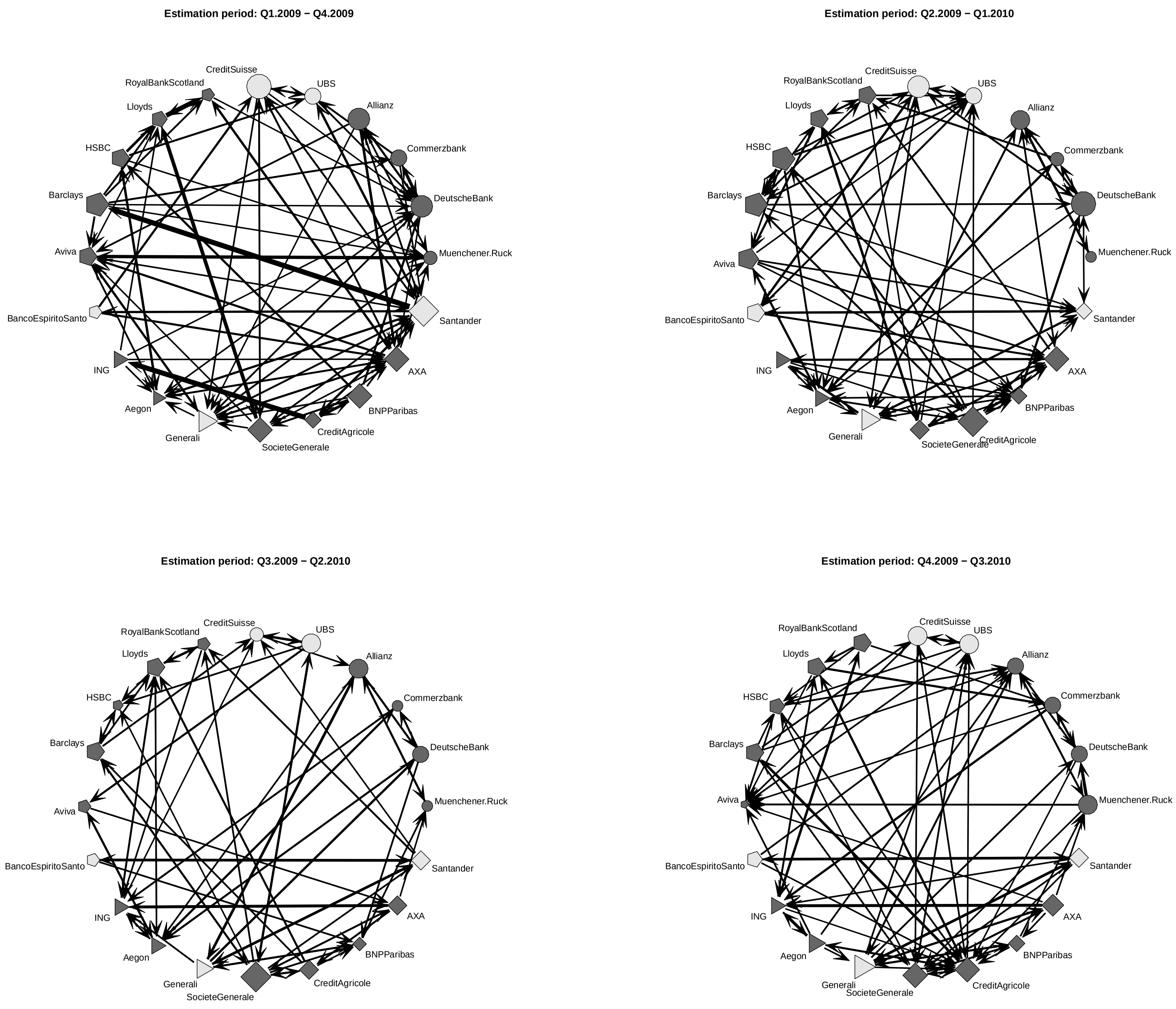

Figure 4: Estimates of yearly systemic risk network rolled over from Q4/2004 to Q3/2010.

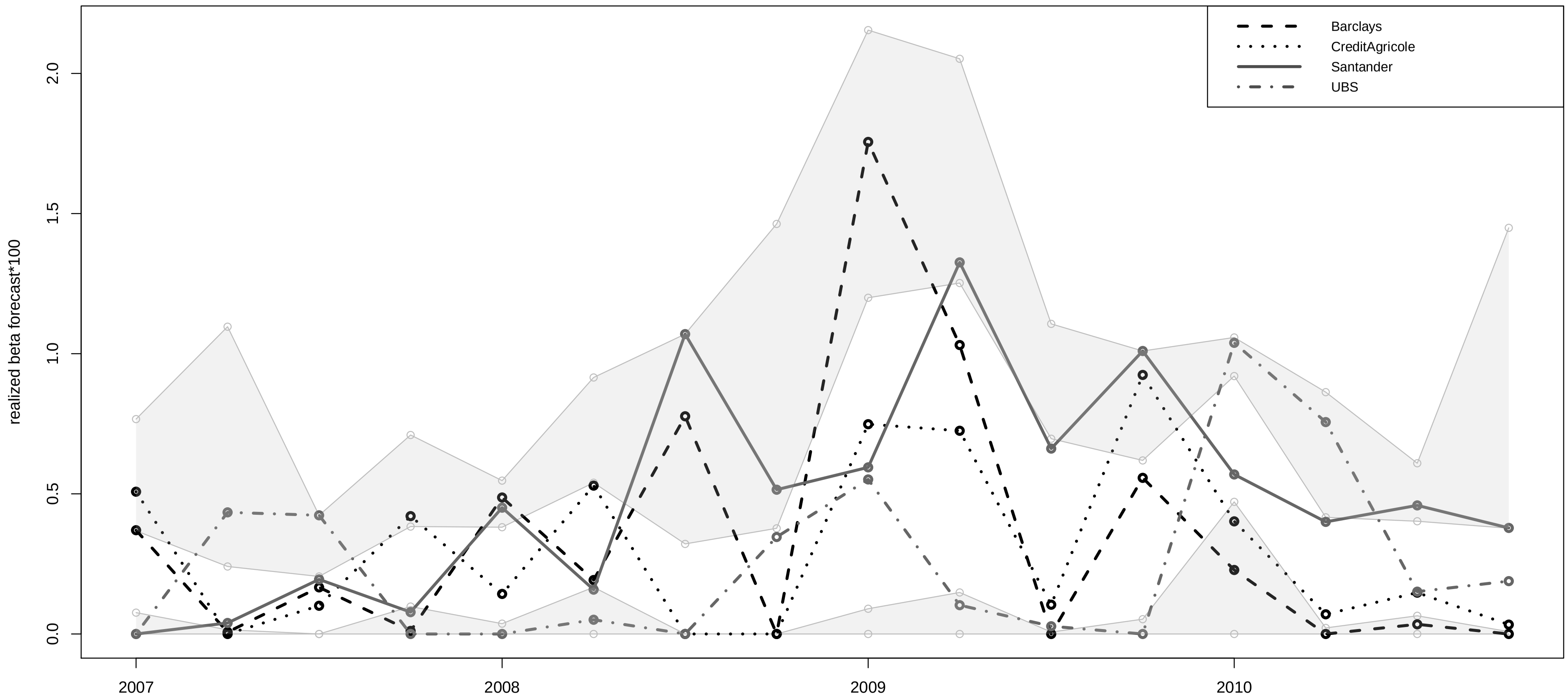

Figure 5: Illustration of time-varying risk rankings, highlighting the evolution of realized systemic risk beta forecasts $\tilde{\beta}$ of four major banks. The upper shaded area depicts the pointwise range between the maximum and the 75%-quantile of $\tilde{\beta}$ for all systemically relevant firms. The lower one marks the corresponding pointwise lower interquartile range of significant realized systemic risk beta forecasts.

Table 2: Systemic risk rankings for 2007 - 2010, based on quarterly realized beta forecasts $\widetilde{\beta}^{s|i} \cdot 100$, see equation 4.[5]

rank	name	forecast	rank	name	forecast
	Q1.2007			Q2.2007	
1	Aegon	0.7667	1	BNP Paribas	1.0964
2	Commerzbank	0.6495	2	UBS	0.434
3	Generali	0.5392	3	Aviva	0.3012
4	Credit Agricole	0.5077	4	Commerzbank	0.276
5	Barclays	0.3703	5	Deutsche Bank	0.2436
6	HSBC	0.3611	6	AXA	0.2324
7	Allianz	0.3492	7	Aegon	0.2095
8	BNP Paribas	0.3016	8	Muenchener Rueck	0.1625
9	Lloyds	0.2887	9	Allianz	0.1252
10	AXA	0.2453	10	ING	0.0914
11	Aviva	0.1888	11	Credit Suisse	0.0865
12	ING	0.163	12	Royal Bank of Scotland	0.051
13	Deutsche Bank	0.1379	13	Santander	0.0393
14	Royal Bank of Scotland	0.0556	14	Barclays	0.0067
	Q3.2007			Q4.2007	
1	UBS	0.4234	1	Deutsche Bank	0.71
2	HSBC	0.3127	2	Aviva	0.5619
3	Deutsche Bank	0.3068	3	Royal Bank of Scotland	0.5504
4	Credit Suisse	0.2296	4	Credit Agricole	0.4205
5	Generali	0.2087	5	BNP Paribas	0.3934
6	Santander	0.1947	6	Credit Suisse	0.3529
7	Barclays	0.1663	7	AXA	0.3306
8	AXA	0.1425	8	HSBC	0.3203
9	ING	0.1203	9	ING	0.3126
10	Credit Agricole	0.1007	10	Aegon	0.3104
11	Commerzbank	0.0681	11	Muenchener Rueck	0.1954
12	Lloyds	0.0672	12	Allianz	0.1594
			13	Commerzbank	0.1045
			14	Lloyds	0.0957
			15	Santander	0.0779
			16	Barclays	0.0109
	Q1.2008			Q2.2008	
1	BNP Paribas	0.5472	1	AXA	0.9152
2	Barclays	0.487	2	Royal Bank of Scotland	0.8259
3	Santander	0.4507	3	Muenchener Rueck	0.7661
4	Commerzbank	0.4375	4	Lloyds	0.5474
5	Deutsche Bank	0.3819	5	Generali	0.543
6	Royal Bank of Scotland	0.3783	6	Credit Agricole	0.5294
7	Credit Suisse	0.3508	7	BNP Paribas	0.5003
8	AXA	0.2114	8	Deutsche Bank	0.4948
9	Credit Agricole	0.1429	9	HSBC	0.4339
10	Muenchener Rueck	0.1351	10	Commerzbank	0.35
11	Allianz	0.1281	11	Aegon	0.2153
12	Lloyds	0.1148	12	Aviva	0.201
13	Aviva	0.071	13	Barclays	0.1925
14	Aegon	0.0255	14	Santander	0.1582
			15	Credit Suisse	0.1427
			16	UBS	0.0508
			17	Allianz	0.0112
	Q3.2008			Q4.2008	
1	Santander	1.07	1	HSBC	1.4631
2	Barclays	0.7768	2	Deutsche Bank	0.6341
3	Aviva	0.4461	3	Santander	0.5148
4	Credit Suisse	0.4029	4	Royal Bank of Scotland	0.4998
5	Generali	0.349	5	BNP Paribas	0.3873
6	Muenchener Rueck	0.2384	6	UBS	0.346
7	Deutsche Bank	0.2113	7	Generali	0.3118
8	HSBC	0.1727	8	Muenchener Rueck	0.2926
9	Royal Bank of Scotland	0.167	9	Lloyds	0.0985
10	ING	0.1566			
11	BNP Paribas	0.0598			

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[5]Avoiding multicollinearity, we include in Z^{i*} only the one component of Z^i which exhibits the lowest correlation with VaR^i in the respective interaction term in (3).

Table 2 – *Continued from previous page*

rank	name	forecast	rank	name	forecast
	Q1.2009			Q2.2009	
1	Aegon	2.1546	1	Aegon	2.0523
2	Barclays	1.7557	2	ING	1.4088
3	AXA	1.5601	3	Lloyds	1.3672
4	Aviva	1.5562	4	BNP Paribas	1.3462
5	Allianz	1.3241	5	Santander	1.3259
6	BNP Paribas	0.8262	6	Barclays	1.031
7	Credit Agricole	0.7485	7	Aviva	0.9001
8	HSBC	0.6697	8	HSBC	0.732
9	Santander	0.5945	9	Credit Agricole	0.7251
10	UBS	0.5514	10	Credit Suisse	0.4722
11	Commerzbank	0.2947	11	Muenchener Rueck	0.4417
12	Generali	0.2347	12	Allianz	0.4111
13	Credit Suisse	0.1561	13	AXA	0.2842
14	Royal Bank of Scotland	0.068	14	UBS	0.1028
15	ING	0.0455	15	Royal Bank of Scotland	0.0619
	Q3.2009			Q4.2009	
1	Commerzbank	1.1065	1	Santander	1.0097
2	Aviva	1.0086	2	Credit Agricole	0.9243
3	ING	0.8852	3	HSBC	0.8437
4	AXA	0.8303	4	BNP Paribas	0.6894
5	Lloyds	0.7041	5	Allianz	0.6225
6	BNP Paribas	0.6744	6	Royal Bank of Scotland	0.6093
7	Santander	0.6615	7	Barclays	0.5571
8	Credit Suisse	0.568	8	Lloyds	0.4588
9	Aegon	0.3393	9	ING	0.3702
10	HSBC	0.284	10	Deutsche Bank	0.3661
11	Credit Agricole	0.1044	11	AXA	0.1541
12	Royal Bank of Scotland	0.0325	12	Generali	0.0858
13	UBS	0.0276	13	Aviva	0.0699
			14	Muenchener Rueck	0.0471
	Q1.2010			Q2.2010	
1	Credit Suisse	1.058	1	Credit Suisse	0.8629
2	Lloyds	1.0418	2	UBS	0.7561
3	Generali	1.0407	3	ING	0.5004
4	UBS	1.0388	4	Aviva	0.4999
5	Aegon	0.9752	5	Generali	0.4217
6	Allianz	0.7554	6	Santander	0.4
7	AXA	0.7471	7	Royal Bank of Scotland	0.3386
8	BNP Paribas	0.6706	8	Aegon	0.2928
9	Santander	0.5692	9	Deutsche Bank	0.2234
10	Commerzbank	0.5583	10	Allianz	0.2227
11	Aviva	0.5208	11	Muenchener Rueck	0.1033
12	HSBC	0.4992	12	Credit Agricole	0.0703
13	ING	0.4722	13	AXA	0.0384
14	Deutsche Bank	0.4712	14	BNP Paribas	0.016
15	Credit Agricole	0.4019			
16	Barclays	0.2284			
17	Royal Bank of Scotland	0.1944			
	Q3.2010			Q4.2010	
1	Aviva	0.6092	1	BNP Paribas	1.4491
2	Generali	0.6008	2	Generali	0.503
3	HSBC	0.4951	3	Muenchener Rueck	0.4914
4	Santander	0.4588	4	Royal Bank of Scotland	0.4371
5	Credit Suisse	0.4493	5	Santander	0.3784
6	Muenchener Rueck	0.261	6	Aviva	0.3737
7	Aegon	0.2226	7	Allianz	0.3589
8	UBS	0.151	8	ING	0.3017
9	Credit Agricole	0.1475	9	AXA	0.2553
10	ING	0.1452	10	UBS	0.1886
11	AXA	0.1233	11	Commerzbank	0.1858
12	Allianz	0.1148	12	Aegon	0.1367
13	Commerzbank	0.0935	13	Credit Agricole	0.0334
14	BNP Paribas	0.0554			
15	Lloyds	0.0426			
16	Barclays	0.0345			
17	Royal Bank of Scotland	0.0222			

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