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 2008-2009, 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, i.e. its potential to significantly increase the risk of failure of the entire system - denoted as systemic risk. 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. Thus realized systemic risk betas measure a firm's contribution to systemic risk which then acts as a measure for its systemic relevance. 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 supervision 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 supervisors 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. It provides an algorithm for model selection and estimation of firm-specific

VaRs and introduces how to estimate and forecast realized systemic risk betas. Section 3 describes the data set. Estimation results, their detailed implications and respective robustness checks are contained in Section 4. Section 5 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 regard 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* dependence structures. We address this issue by a time-dependent selection of relevant risk drivers $R^{(i,t)}_t$ 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 12 months 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

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

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.

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 R_t is a K-vector of centered observations of the potential regressors. 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 $\widehat{\xi^{it_0}_q}(c_2)$. Apply an F-test for joint significance of regressors $R^{(i,t_0)}(c_2 \backslash c_1)$. 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 $R^{(i,t_0)}(c_l)$ with corresponding post-LASSO estimates $\widehat{\xi^{it_0}_q}(c_l)$ for the coefficients.

Note that we aim at keeping the model parsimonious. Therefore we set the significance level underlying the F-test in Step 3 to 5%. This corresponds to the minimum feasible level still guaranteeing stability of the procedure given the available sample size and the substantial correlation structure of regressors in the LASSO selection step. We found that imposing higher accuracy of lower F-test levels, tends to induce robustness problems such as non-nested models in the sequential upward procedure. In contrast, higher significance levels generally result in larger systemic risk networks corresponding to a wider view of potential “relevance”.

2.2. Forecasting Systemic Impact

In an interconnected financial system, we measure the systemic risk 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.[1] 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

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

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

[1]Please note that we use the terms ‘systemic impact’, ‘systemic relevance’, and ‘systemic risk (contribution)’ synonymously.

3. Data

Our sample of financial firms comprises 20 European banks and insurance companies. A list can be found in Table 2. 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.[2] 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.[3]

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

[2]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.

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

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.

4. Results

4.1. Time-varying tail risk networks

Having identified the tail risk drivers for each firm allows 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 4 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.

With our analysis we can statistically determine "relevant" (directed) risk connections in the financial network. Identifying the underlying *economic* causes for a link between two companies, however, is more difficult given the available data. Nevertheless, the inclusion of firm-specific characteristics and macroeconomic state variables allows us to a certain extent to control for situations where firms have (similar) exposure to the same risk factors. Such factors cause bi-directional relationships due to firms' dependence on common situations, such as, for instance, periods of high volatility, flattening of yield curves, increased sovereign default or falling overall credit quality. Accordingly, the identified risk connections are *not* due to companies' exposure to same economic conditions or risk factors as captured by the included control variables, but are caused by (possibly remaining) factors inherently related to inter-bank connections. These are most likely counterparty relations (i.e., one firm is the counterparty of the other) and/or the same exposure to toxic assets in firms' balance sheets.

In this spirit, we identify several risk connections which remain quite stable over time and thus appear as fundamental risk channels of the European financial network during the period under consideration. An interesting such case is the tail risk connection 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. Hence, governmental support of Commerzbank was an important step to reduce its systemic risk contribution. This is empirically in line with our study as we observe a declining tail risk connectedness of Commerzbank after the bailout. Persistent risk connections are also identified between Royal Bank of Scotland (RBS) and Barclays. Despite their perceived quite different situation (see Table 1), 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

Table 1: Schematic overview of the situation of two UK banks during the sample period.

RBS	Barclays
April 2008: substantial write-downs due to break-down of U.S. housing and credit markets	*April 2008* and before: relatively well funded, even explored options to take over Lehman Brothers
Start 2009: record loss, bailed out by UK government (stake increase to 70%)	*Fall 2008*: raise of new capital by investors
	Start 2009: no participation in government's insurance schemes for toxic assets required.

financial crisis. Probably caused by counterparty relations, RBS received substantial tail risk from Barclays further increasing RBS's potential losses and making both companies systemically risky. 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.

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.

Although all of 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 industryspecific 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 which is likely to be caused by exposure to the same classes of toxic assets.

Our approach, however, also captures interesting time variations in tail risk channels. In particular, in 2008/09, we observe high fluctuations of network connections which are likely to be caused by counterparty relations in combination with funding liquidity shortages. Accordingly, they vanished in the aftermath of the crisis. 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.

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.

4.2. Systemic risk rankings

After having determined individual companies' VaRs, realized systemic risk betas can be estimated and forecasts for each quarter can be computed according to equation 4. Table 4 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 4 should rather be seen as an indication for a company's relative systemic importance characterizing groups of similar relative systemic impact. We therefore suggest a "traffic light system" of high, medium and low ranked systemically risky banks as reported in Table 3. [4] Clearly, when a financial firm is distressed, bailout decisions should not be based solely on this categorization at the respective point in time. Instead,

[4]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.

the evolvement of the measure should be observed over time and past periods should be taken into consideration, in order to obtain a full picture of the firm's systemic impact.

Figure 5 illustrates the time-varying cross-sectional distribution of the estimated betas and the three traffic light groups. 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.

These effects are supported by the pointwise, ungrouped results in Table 4 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). Note that the high variation of pointwise predicted systemic risk betas is neither an artefact of the LASSO-procedure for network selection nor an indication of problems in selecting the penalization constant in practice. Plots of estimated individual VaRs rather reveal a major part of the volatile behavior stemming from the hard thresholding with which other companies' loss exceedances are measured and thus appear and disappear as potential candidates for network links over time. We leave it for future work to determine appropriate smoothed versions of exceedances. In our study we remain conservative towards the type II error in detecting network links and keep the extreme cut-off behavior where firms can only be risk drivers if in distress and not on the way towards potential distress. Our recommended classification of firms for supervisors in this setting is thus broad and groupwise as shown in Table 3.

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, particularly 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. 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. 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.

To analyze whether systemic risk betas are related to companies' balance sheet characteristics, we compare rankings of quarterly averaged realized systemic risk beta estimates to rankings according firms' size, leverage, and maturity mismatch. In particular, we estimate Kendall's rank correlation coefficient according to

$$\widehat{\tau} = \frac{\text{number of concordant pairs} - \text{number of discordant pairs}}{0.5n(n-1)}.$$

$\widehat{\tau}$ is known to be more robust towards deviations from normality than the Pearson correlation coefficient (see, e.g., Dehling, Vogel, Wendler, and Wied (2012), and aims directly at comparing the ordering of variables.

To distinguish between a pre-crisis and (post) crisis period, we compute Kendall's τ for pooled data from 2006 to the end of 2007 (8 quarters) as well as for the subsequent period including the crisis and its aftermath (12 quarters). Table 5 reports the estimated rank correlations together with the outcomes of one-sided significance tests, with the null hypothesis $H_0 : \tau \leq 0$. Based on the pre-crisis period, we find that correlations of 0,11 between systemic risk betas and leverage as well as maturity mismatch are significant at a 5% level, whereas the correlation with size is smaller and only significant at 10%. These results indicate that even in non-crisis periods mainly network effects do drive predictions of systemic relevance in realized systemic risk betas rather than idiosyncratic characteristics. Within the firm specific effects, we also find that size is not the dominating factor which is in contrast to the well-known ”to big to fail” statement. Important idiosyncratic risk drivers are rather leverage and funding risk, approximated by maturity mismatch. During the (post) crisis period, estimated correlations become insignificant and are virtually zero. This shows that from 2008 onwards, the influence of observable firm characteristics even decreases further and network connections are the pre-dominant drivers for short-term predictions of firm's systemic riskiness. This also corresponds to a sharp increase of realized systemic risk beta forecasts as shown in Figure 5.

4.3. Out-of-sample validation of forecasts

A direct evaluation of realized systemic risk beta forecasts is not possible, since they cannot be observed even ex post. As systemic risk betas measure the effect of firms' tail risk on the tail risk of the system, an observable proxy benchmark is the tail correlation between the system return and each individual company's return. Accordingly, for a first rough forecast validation setting, we compute quarterly tail correlations based on 10% quantiles balancing the need of a sufficient number of observations on the one hand and the need to capture *tail* risk. In particular, we estimate the correlations for each quarter k as

$$\bar{\rho}_k^{s,i} = \text{corr}_k \left(X^s, X^i | X^s < q_{0.1}(X^s), X^i < q_{0.1}(X^i) \right),$$

for from observations X_t^s, X_t^i with $t = t_{0,k} + 1, ..., t_{0,k} + \tilde{\tau}_k$ for each end-of-quarter time point $t_{0,k}$, where $\tilde{\tau}_k$ denotes the length of the next quarter, using the Pearson correlation coefficient, see e.g. Ang and Chen (2002).

As a naive benchmark for assessing a firms' marginal relevance in the financial system, we compute a simple financial system CAPM-type beta defined as the slope coefficient in time series regressions of individual returns on the system return. We take this simplistic competitor as a lower bound benchmark, which is much easier to obtain than our realized systemic risk beta but is obviously ”naive” as it does not account for tail dependencies but just mean dependencies and reverts the causality between system returns and individual returns. To evaluate the two different forecasts, we compute the R^2 in separate forecast regressions of the form

$$\widehat{\rho}_k^{s,i} = \gamma_0 + \gamma_1 b_k^i + \varepsilon_k^{s,i} \tag{6}$$

where k is the quarter index and $b^i \in \left\{\widetilde{\beta}^{s|i}_{t_0+\tilde{\tau}|t_0}, \beta^{CAPM,i}_{t_0+\tilde{\tau}|t_0}\right\}$. The higher the respective R^2, the more variation in future tail correlation is explained by the respective systemic risk forecast. Boxplots of all R^2s for the different companies are shown in Figure 6. It turns out that the realized systemic risk beta clearly outperforms the "financial system beta" in forecasting future tail dependence between the system and individual banks and insurance companies.

In a second forecast evaluation scenario, we study the ability of the two measures to explain variations in returns in periods of extreme (negative) realizations denoted as the 10% worst outcomes of equity returns for each firm. Accordingly, we take the average 10% loss exceedances $\bar{Ex}^i$ of all firms in the quarter k following the estimation period, and run cross-sectional regressions thereof on the respective realizations of the two competing betas,

$$\bar{Ex}_k^i = \zeta_0 + \zeta_1 b_k^i + \varepsilon_t^{s,i}, \tag{7}$$

with b_k^i defined as above. Such a regression has some analogy to a typical second pass CAPM regression linking cross-sectional variations in excess returns to the cross-sectional variation in market betas. Although the systemic risk beta is not tailored to such a setting, our findings in Figure 7 show that on average it provides a better prediction of extreme market valuations than a the simple financial system CAPM-type beta.

5. 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, vary substantially over time in the considered hard-thresholding case for cross-effects. Therefore forecasting stability and responsiveness require careful balancing and yield a traffic light system for systemic risk forecasts. 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 supervision authorities. 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 2: 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)	Munich Re (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)

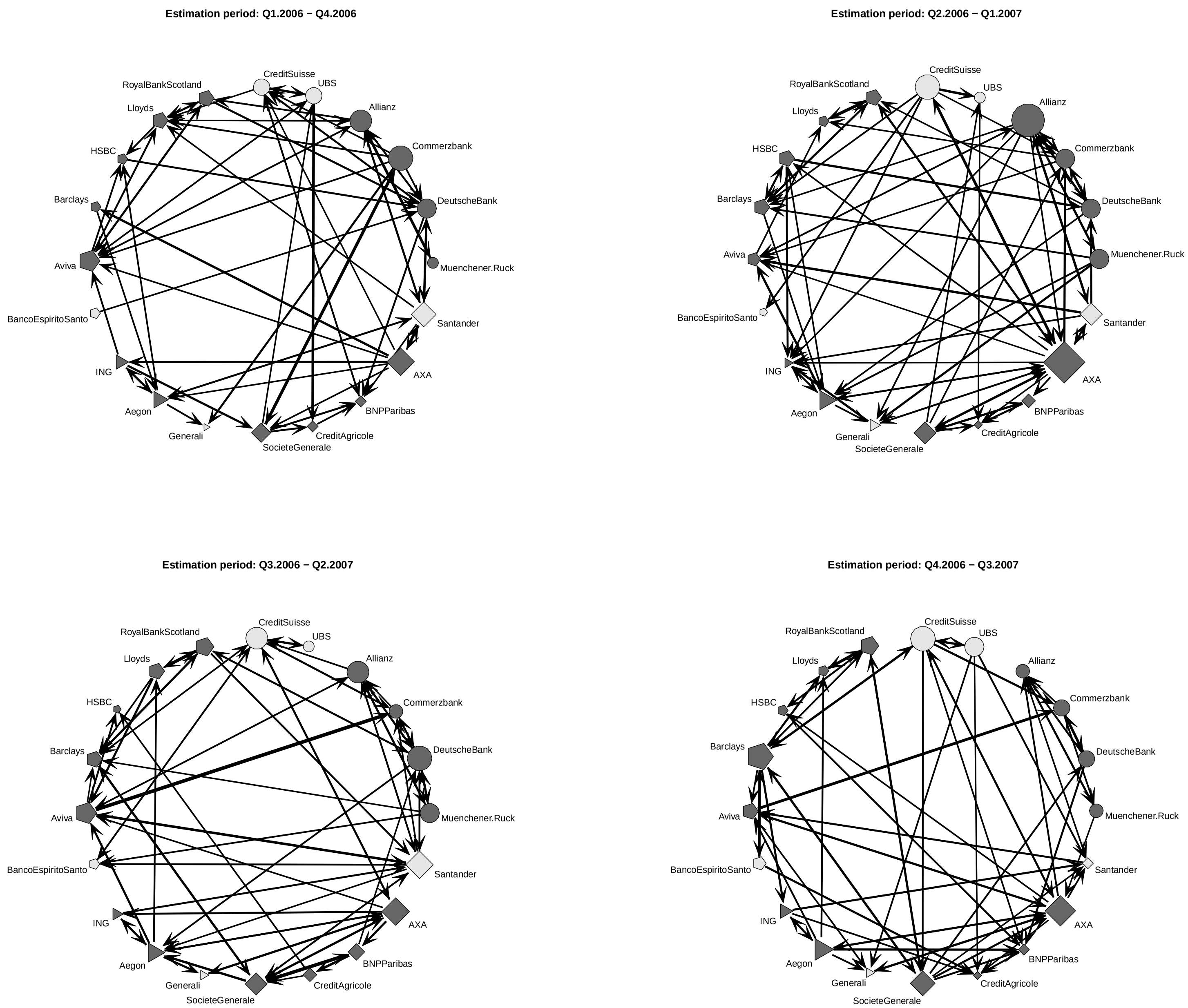

Figure 1: Estimates of yearly systemic risk network rolled over from Q4/2006 to Q3/2007

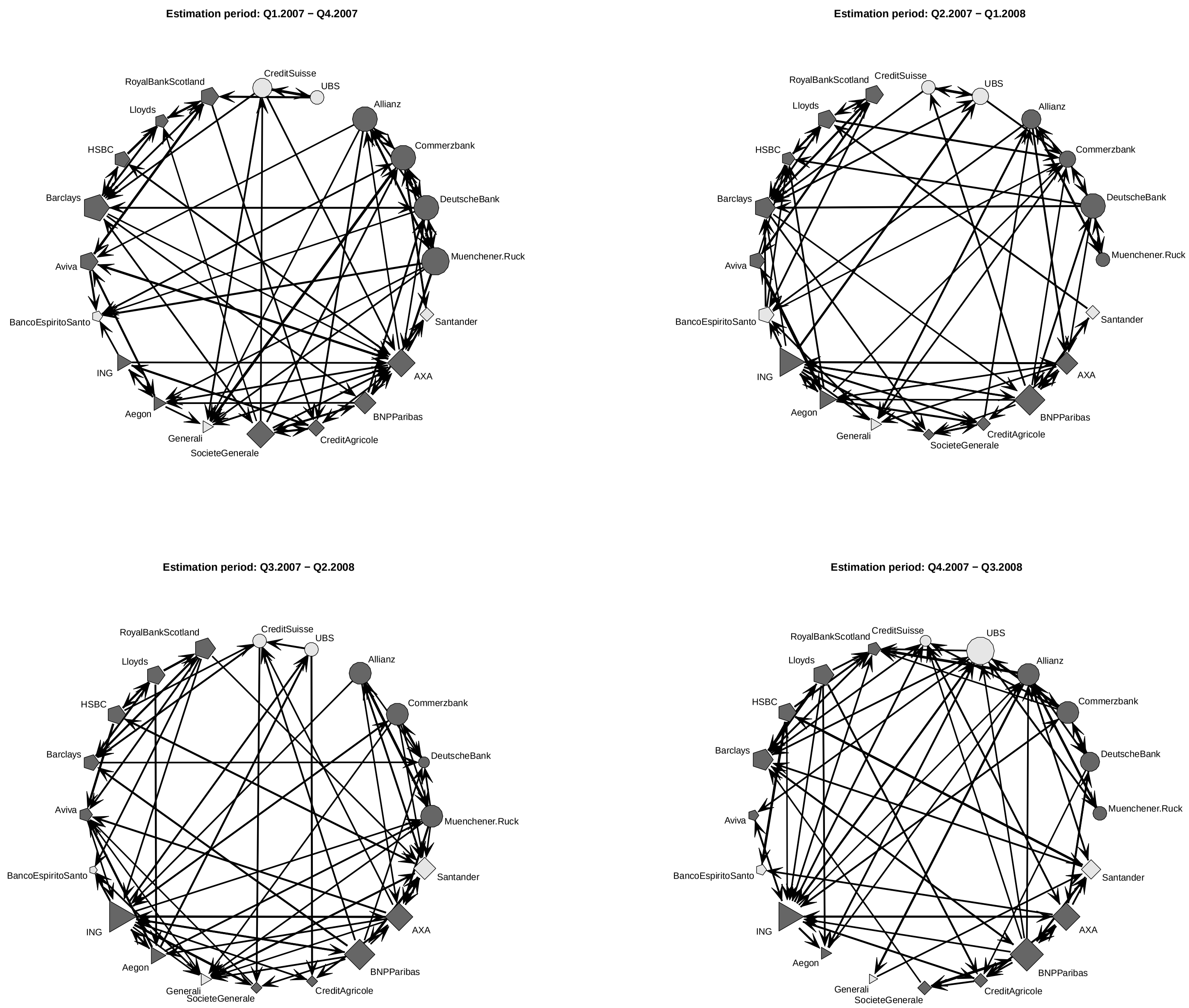

Figure 2: Estimates of yearly systemic risk network rolled over from Q4/2007 to Q3/2008.

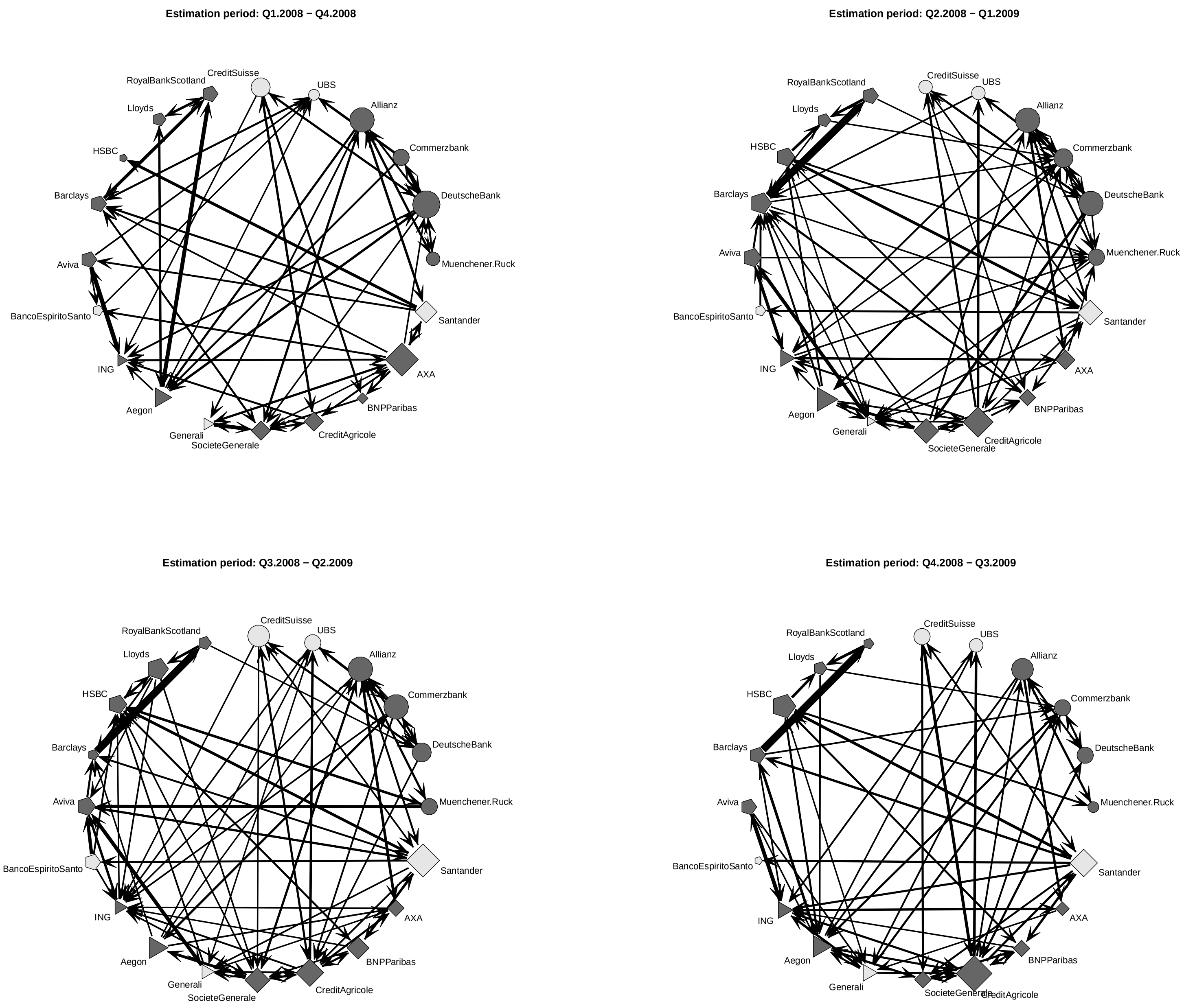

Figure 3: Estimates of yearly systemic risk network rolled over from Q4/2008 to Q3/2009.

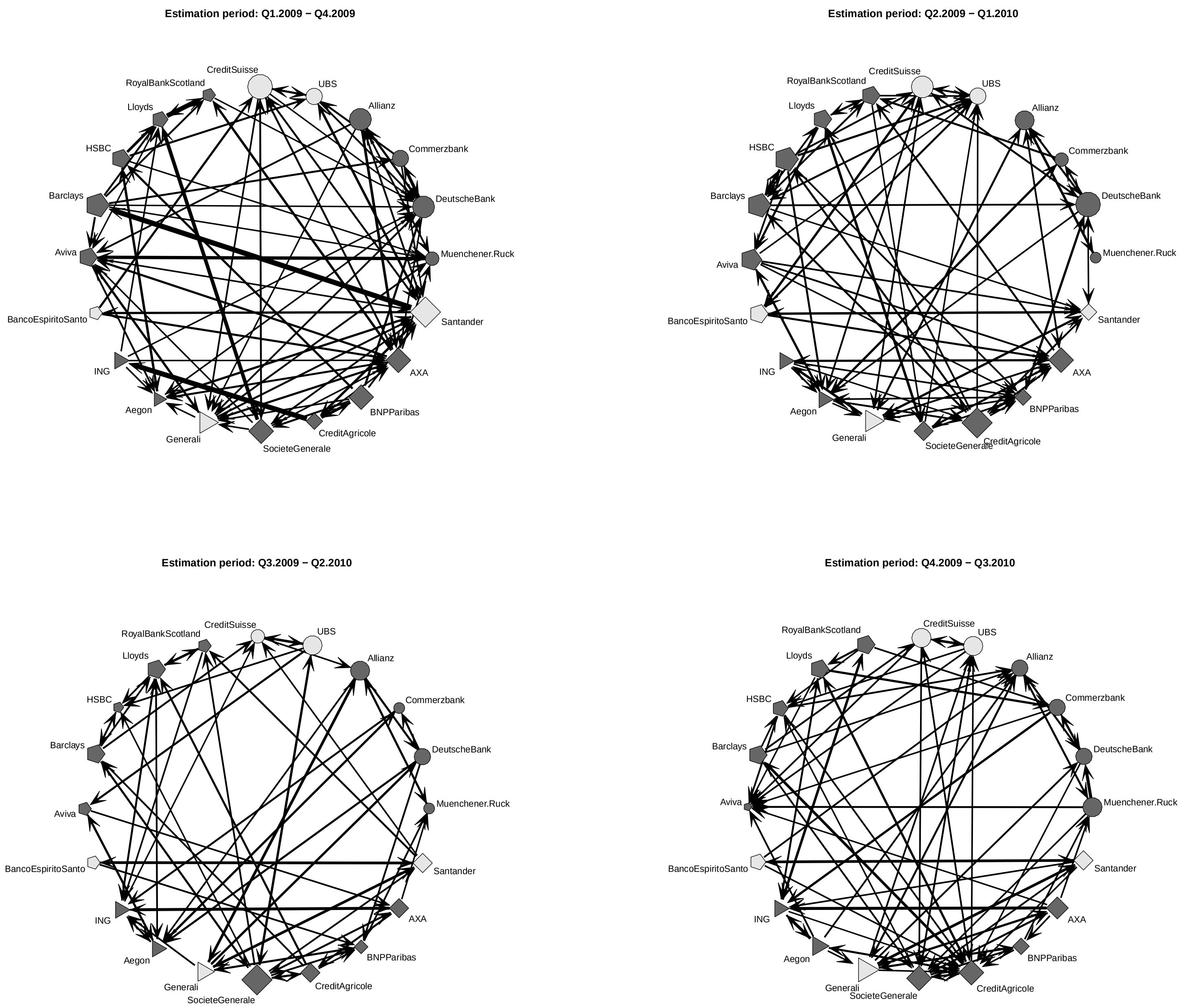

Figure 4: Estimates of yearly systemic risk network rolled over from Q4/2004 to Q3/2010.

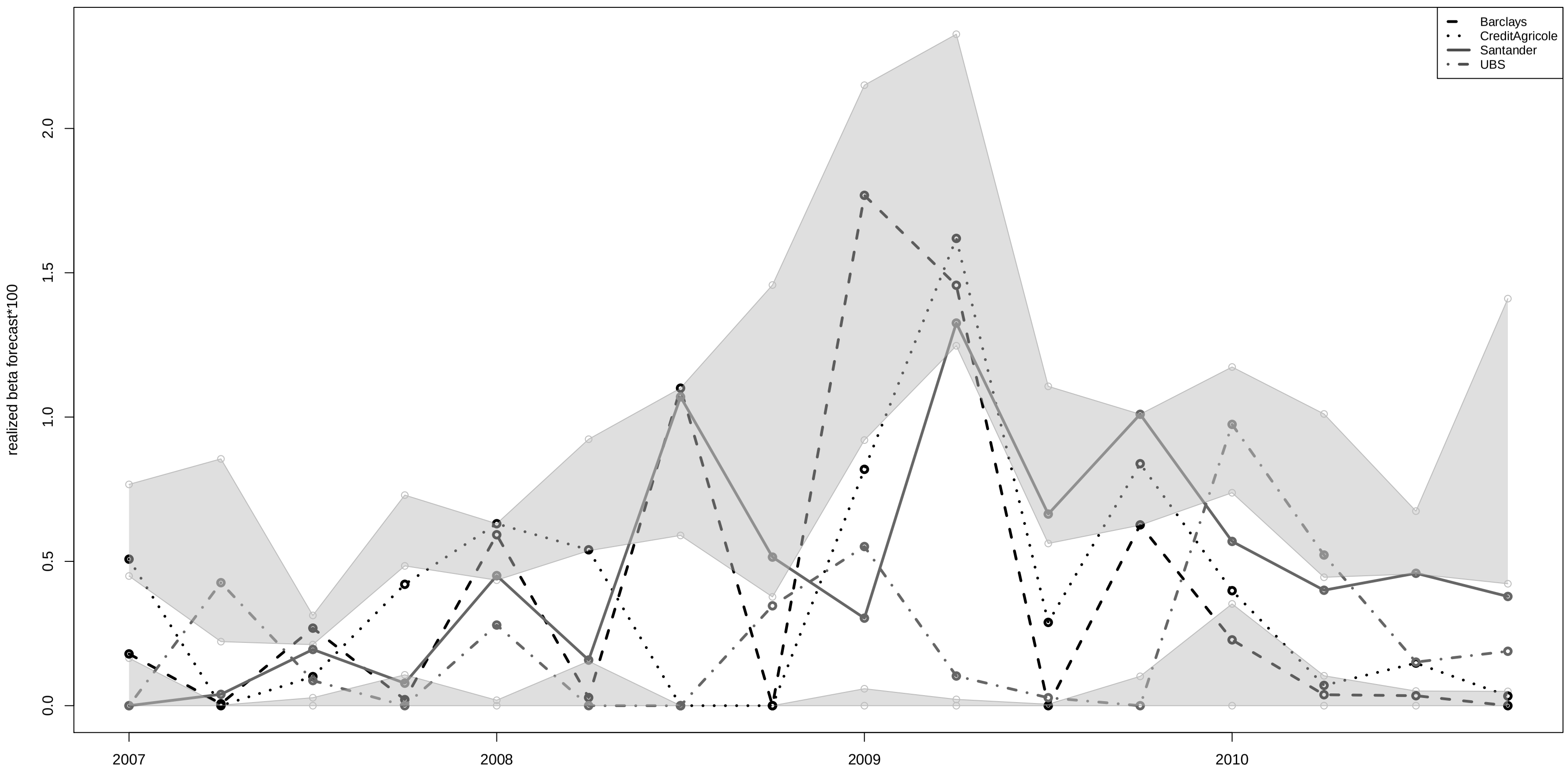

Figure 5: Illustration of time-varying risk rankings, highlighting the evolution of realized systemic risk beta forecasts $\tilde{\beta}$ of four major banks. The upper shaded area depicts the pointwise range between the maximum and the 75%-quantile of $\tilde{\beta}$ for all systemically relevant firms.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

Table 3: Group rankings of systemically risky companies, according to their quarterly realized systemic risk beta forecasts $\widetilde{\beta}^{s|i}$ (see equation 4). 'High' systemic risk is reflected by a realized systemic risk beta above the 75% quantile of all realized systemic risk betas at the respective end-of-quarter time point. Companies listed in the 'medium' group have realized systemic risk betas above the 25% quantile but below the 75% quantile. 'Low' represents the ones below the 25% quantile.

	Q1.2007
high	Aegon, Allianz, Commerzbank, CreditAgricole, Generali
med.	Aviva, AXA, Barclays, BNPParibas, HSBC, ING, Lloyds, RoyalBankScotland
low	CreditSuisse, DeutscheBank, Munich Re, Santander, UBS
	Q2.2007
high	Aviva, BNPParibas, Commerzbank, DeutscheBank, UBS
med.	Aegon, Allianz, AXA, Barclays, CreditSuisse, ING, Munich Re, Santander
low	CreditAgricole, Generali, HSBC, Lloyds, RoyalBankScotland
	Q3.2007
high	AXA, Barclays, DeutscheBank, HSBC, ING
med.	Aviva, CreditAgricole, CreditSuisse, Generali, Lloyds, RoyalBankScotland, Santander, UBS
low	Aegon, Allianz, BNPParibas, Commerzbank, Munich Re
	Q4.2007
high	Aviva, AXA, BNPParibas, DeutscheBank, RoyalBankScotland
med.	Aegon, Allianz, Commerzbank, CreditAgricole, CreditSuisse, HSBC, ING, Munich Re
low	Barclays, Generali, Lloyds, Santander, UBS
	Q1.2008
high	Barclays, Commerzbank, CreditAgricole, CreditSuisse, Santander
med.	Aegon, Aviva, BNPParibas, DeutscheBank, Lloyds, Munich Re, RoyalBankScotland, UBS
low	Allianz, AXA, Generali, HSBC, ING
	Q2.2008
high	AXA, CreditAgricole, Generali, Munich Re, RoyalBankScotland
med.	Aegon, Aviva, BNPParibas, Commerzbank, DeutscheBank, HSBC, Lloyds, Santander
low	Allianz, Barclays, CreditSuisse, ING, UBS
	Q3.2008
high	Aviva, Barclays, CreditSuisse, DeutscheBank, Santander
med.	BNPParibas, Commerzbank, Generali, HSBC, ING, Lloyds, Munich Re, RoyalBankScotland
low	Aegon, Allianz, AXA, CreditAgricole, UBS
	Q4.2008
high	BNPParibas, DeutscheBank, HSBC, RoyalBankScotland, Santander
med.	Allianz, AXA, Commerzbank, Generali, ING, Lloyds, Munich Re, UBS
low	Aegon, Aviva, Barclays, CreditAgricole, CreditSuisse
	Q1.2009
high	Aegon, Aviva, AXA, Barclays, BNPParibas
med.	Allianz, Commerzbank, CreditAgricole, Generali, HSBC, RoyalBankScotland, Santander, UBS
low	CreditSuisse, DeutscheBank, ING, Lloyds, Munich Re
	Q2.2009
high	Aegon, Barclays, CreditAgricole, ING, Santander
med.	Allianz, Aviva, AXA, BNPParibas, HSBC, Lloyds, Munich Re, UBS
low	Commerzbank, CreditSuisse, DeutscheBank, Generali, RoyalBankScotland
	Q3.2009
high	Aviva, Commerzbank, ING, Lloyds, Santander
med.	Aegon, AXA, BNPParibas, CreditAgricole, CreditSuisse, HSBC, RoyalBankScotland, UBS
low	Allianz, Barclays, DeutscheBank, Generali, Munich Re
	Q4.2009
high	Barclays, BNPParibas, CreditAgricole, HSBC, Santander
med.	Allianz, Aviva, AXA, DeutscheBank, ING, Lloyds, Munich Re, RoyalBankScotland
low	Aegon, Commerzbank, CreditSuisse, Generali, UBS
	Q1.2010
high	Allianz, AXA, Generali, Lloyds, UBS
med.	BNPParibas, Commerzbank, CreditAgricole, CreditSuisse, DeutscheBank, HSBC, ING, Santander
low	Aegon, Aviva, Barclays, Munich Re, RoyalBankScotland
	Q2.2010
high	Aviva, CreditSuisse, DeutscheBank, ING, UBS
med.	Aegon, Allianz, AXA, BNPParibas, Generali, HSBC, RoyalBankScotland, Santander
low	Barclays, Commerzbank, CreditAgricole, Lloyds, Munich Re
	Q3.2010
high	Aviva, AXA, Generali, HSBC, Santander
med.	Aegon, Allianz, Commerzbank, CreditAgricole, CreditSuisse, ING, Munich Re, UBS
low	Barclays, BNPParibas, DeutscheBank, Lloyds, RoyalBankScotland
	Q4.2010
high	Aviva, BNPParibas, Generali, Munich Re, RoyalBankScotland
med.	Aegon, Allianz, AXA, Commerzbank, CreditSuisse, ING, Santander, UBS
low	Barclays, CreditAgricole, DeutscheBank, HSBC, Lloyds

Table 4: Systemic risk rankings for 2007 - 2010, based on quarterly realized beta forecasts $\widetilde{\beta}^{s|i} \cdot 100$, see equation 4.[6]

rank	**name**	**forecast**	**rank**	**name**	**forecast**
	Q1.2007			Q2.2007	
1	Aegon	0.7667	1	BNPParibas	0.8551
2	Commerzbank	0.6819	2	UBS	0.4262
3	Generali	0.5671	3	Aviva	0.2844
4	CreditAgricole	0.5077	4	Commerzbank	0.2732
5	Allianz	0.4704	5	DeutscheBank	0.2381
6	BNPParibas	0.3858	6	AXA	0.1734
7	HSBC	0.3611	7	Munich Re	0.1625
8	Royal Bank of Scotland	0.3472	8	Aegon	0.1332
9	Lloyds	0.2887	9	Allianz	0.1224
10	Aviva	0.2615	10	CreditSuisse	0.0952
11	AXA	0.2584	11	ING	0.0513
12	Barclays	0.1794	12	Santander	0.0393
13	ING	0.1651	13	Barclays	0.0067
14	DeutscheBank	0.1645			
15	CreditSuisse	0.0358			
	Q3.2007			Q4.2007	
1	HSBC	0.3127	1	DeutscheBank	0.7296
2	DeutscheBank	0.3068	2	Aviva	0.5705
3	ING	0.2849	3	Royal Bank of Scotland	0.5701
4	Barclays	0.2687	4	AXA	0.5556
5	AXA	0.2125	5	BNPParibas	0.5056
6	Generali	0.2087	6	CreditAgricole	0.4205
7	CreditSuisse	0.2016	7	CreditSuisse	0.3586
8	Santander	0.1947	8	HSBC	0.3203
9	Aviva	0.1726	9	Aegon	0.3123
10	CreditAgricole	0.1007	10	ING	0.2791
11	Royal Bank of Scotland	0.0906	11	Allianz	0.2584
12	UBS	0.087	12	Munich Re	0.1954
13	Lloyds	0.0672	13	Commerzbank	0.14
14	Commerzbank	0.0143	14	Lloyds	0.0957
			15	Santander	0.0779
			16	Barclays	0.021
	Q1.2008			Q2.2008	
1	CreditAgricole	0.6305	1	AXA	0.9233
2	CreditSuisse	0.6101	2	Royal Bank of Scotland	0.8246
3	Barclays	0.5923	3	Munich Re	0.7661
4	Commerzbank	0.5167	4	Generali	0.543
5	Santander	0.4507	5	CreditAgricole	0.5402
6	BNPParibas	0.3875	6	Lloyds	0.5272
7	Royal Bank of Scotland	0.3754	7	BNPParibas	0.412
8	DeutscheBank	0.3482	8	DeutscheBank	0.3884
9	UBS	0.2794	9	Aviva	0.2378
10	Aviva	0.2606	10	Commerzbank	0.2346
11	Munich Re	0.1351	11	HSBC	0.2261
12	Lloyds	0.1148	12	Aegon	0.1683
13	Aegon	0.0255	13	Santander	0.1582
14	HSBC	0.0166	14	CreditSuisse	0.1527
			15	Barclays	0.028
			16	UBS	1e-04
	Q3.2008			Q4.2008	
1	Barclays	1.1002	1	HSBC	1.4576
2	Santander	1.07	2	DeutscheBank	1.3393
3	Aviva	0.695	3	Santander	0.5148
4	CreditSuisse	0.6931	4	Royal Bank of Scotland	0.4998
5	DeutscheBank	0.611	5	BNPParibas	0.3873
6	ING	0.5266	6	UBS	0.346
7	Lloyds	0.3671	7	Generali	0.3118
8	Generali	0.349	8	Munich Re	0.2926
9	HSBC	0.3427	9	AXA	0.2877
10	Royal Bank of Scotland	0.2964	10	ING	0.0797
11	Munich Re	0.2384	11	Lloyds	0.0626
12	BNPParibas	0.1691			

Continued on next page

Table 4 – *Continued from previous page*

rank	name	forecast	rank	name	forecast
	Q1.2009			Q2.2009	
1	Aegon	2.15	1	Aegon	2.3266
2	Barclays	1.7684	2	CreditAgricole	1.6192
3	Aviva	1.5562	3	ING	1.4976
4	AXA	1.4611	4	Barclays	1.4567
5	BNPParibas	0.9237	5	Santander	1.3259
6	Allianz	0.91	6	Lloyds	1.0107
7	CreditAgricole	0.8189	7	AXA	0.4753
8	HSBC	0.6697	8	HSBC	0.4607
9	UBS	0.5514	9	Munich Re	0.4417
10	Commerzbank	0.3426	10	Allianz	0.4111
11	Santander	0.3033	11	BNPParibas	0.3134
12	Royal Bank of Scotland	0.2653	12	UBS	0.1028
13	Generali	0.2347	13	Aviva	0.0869
	Q3.2009			Q4.2009	
1	Commerzbank	1.1065	1	Santander	1.0097
2	ING	0.764	2	HSBC	0.8452
3	Aviva	0.7615	3	CreditAgricole	0.8385
4	Santander	0.6639	4	BNPParibas	0.701
5	Lloyds	0.5824	5	Barclays	0.6265
6	CreditSuisse	0.5009	6	Allianz	0.6225
7	BNPParibas	0.4688	7	Royal Bank of Scotland	0.6223
8	AXA	0.3878	8	Lloyds	0.4773
9	Aegon	0.3393	9	Munich Re	0.4717
10	HSBC	0.3103	10	ING	0.4241
11	CreditAgricole	0.2886	11	DeutscheBank	0.3327
12	UBS	0.0276	12	Aviva	0.2057
13	Royal Bank of Scotland	0.02	13	AXA	0.1675
			14	Generali	0.0797
	Q1.2010			Q2.2010	
1	Commerzbank	1.1065	1	Santander	1.0097
2	ING	0.764	2	HSBC	0.8452
3	Aviva	0.7615	3	CreditAgricole	0.8385
4	Santander	0.6639	4	BNPParibas	0.701
5	Lloyds	0.5824	5	Barclays	0.6265
6	CreditSuisse	0.5009	6	Allianz	0.6225
7	BNPParibas	0.4688	7	Royal Bank of Scotland	0.6223
8	AXA	0.3878	8	Lloyds	0.4773
9	Aegon	0.3393	9	Munich Re	0.4717
10	HSBC	0.3103	10	ING	0.4241
11	CreditAgricole	0.2886	11	DeutscheBank	0.3327
12	UBS	0.0276	12	Aviva	0.2057
13	Royal Bank of Scotland	0.02	13	AXA	0.1675
			14	Generali	0.0797
	Q3.2010			Q4.2010	
1	Aviva	0.6742	1	BNPParibas	1.4104
2	Generali	0.6008	2	Generali	0.503
3	AXA	0.5016	3	Munich Re	0.4914
4	HSBC	0.4951	4	Aviva	0.4862
5	Santander	0.4588	5	RoyalBankScotland	0.4371
6	CreditSuisse	0.4493	6	Santander	0.3784
7	Munich Re	0.261	7	Allianz	0.3589
8	Aegon	0.2226	8	AXA	0.2553
9	ING	0.21	9	ING	0.2052
10	UBS	0.151	10	UBS	0.1886
11	CreditAgricole	0.1475	11	Aegon	0.1367
12	Allianz	0.1148	12	CreditSuisse	0.1355
13	Commerzbank	0.0749	13	Commerzbank	0.0979
14	Lloyds	0.0426	14	CreditAgricole	0.0334
15	Barclays	0.0345			
16	RoyalBankScotland	0.0222			

[6] 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).

Figure 6: Boxplots of R^2 from forecast regressions according to equation 6.

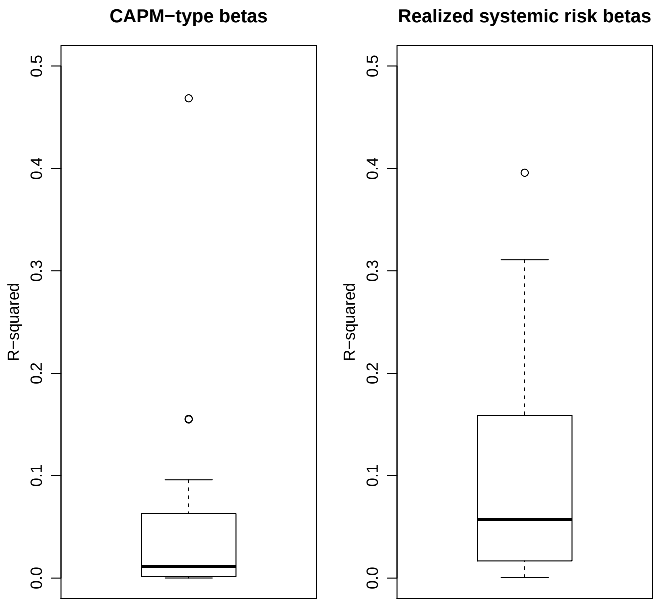

Figure 7: Boxplots of R^2 from forecast regressions according to equation 7.

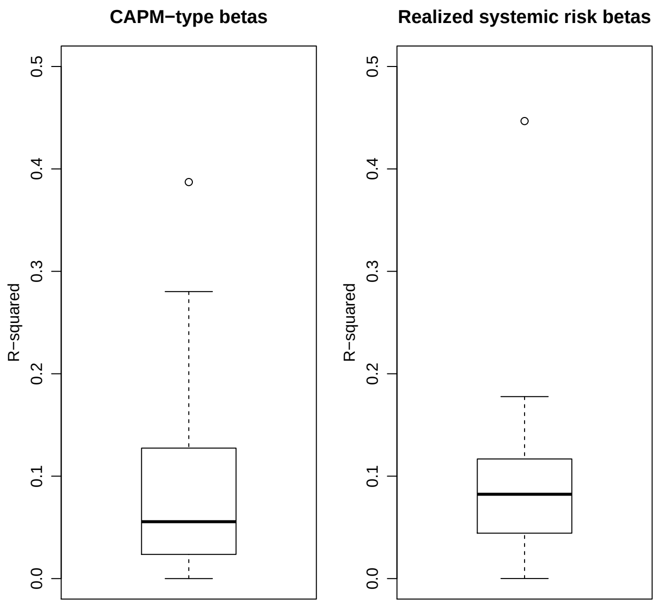

Table 5: Estimated rank correlation (Kendall's τ) between three quarterly balance sheet characteristics and average realized systemic risk betas.

firm characteristic	$\widehat{\tau}$-rank correlation with $\widetilde{\beta}^{s\|i}$ for pooled data	
	Q1/2006-Q4/2007	Q1/2008-Q4/2010
size	0.07**	-
leverage	0.11***	-
maturity mismatch	0.11***	-

** /***: p-val. ($H_0 : \tau \leq 0$) significant at 10% / 5%. - : p-val. ($H_0 : \tau \leq 0$) not rejected at 30% .

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