Financial Network Systemic Risk Contributions *

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Abstract

We propose the *realized systemic risk beta* as a measure for financial companies' contribution to systemic risk given network interdependence between firms' tail risk exposures. Conditional on statistically pre-identified network spillover effects and market and balance sheet information, we define the realized systemic risk beta as the total time-varying marginal effect of a firm's Value-at-risk (VaR) on the system's VaR. Suitable statistical inference reveals a multitude of relevant risk spillover channels and determines companies' systemic importance in the U.S. financial system. Our approach can be used to monitor companies' systemic importance allowing for a transparent macroprudential regulation.

Keywords: Systemic risk contribution, systemic risk network, Value at Risk, network topology, two-step quantile regression, time-varying parameters

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

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The financial crisis 2007-2009 has shown that cross-sectional dependencies between assets and credit exposures can cause even small risks of individual banks to cascade and build up to a substantial threat for the stability of an entire financial system.[1] Under certain economic conditions, company-specific risk cannot be appropriately assessed in isolation without accounting for potential risk spillover effects from other firms. In fact, it is not just its size and idiosyncratic risk but also its interconnectedness with other firms which determines a company's systemic relevance i.e., its potential to significantly increase the risk of failure of the entire system – which we denote as systemic risk.[2] While there is a broad consensus that any prudential regulatory policy should account for the consequences of network interdependencies in the financial system, in practice, however, any attempt of a transparent implementation must fail, as long as suitable empirical measures for firms' individual risk, risk spillovers and systemic relevance are not available. In particular, it is unclear how to quantify individual risk exposures and systemic risk contributions in an appropriate but still parsimonious and empirically tractable way for a prevailing underlying network structure. And there is an apparent need for respective empirically feasible and forward-looking measures which only rely on available data of publicly disclosed balance sheet and market information but still account for the complexity of the financial system.

A general empirical assessment of systemic relevance cannot build on the vast theoretical literature of financial network models and financial contagion, since these results typically require detailed information on intra-bank asset and liability exposures (see, e.g., Allen and Gale, 2000, Freixas, Parigi, and Rochet, 2000, and Leitner, 2005). Such data is generally not publicly disclosed and even regulators can only collect partial information on some sources of inter-bank linkages. Available empirical studies linked to this literature can therefore only partially contribute to a full picture of companies' systemic relevance as they focus on particular parts of specific markets at a particular time under particular financial conditions (see, e.g., Upper and Worms, 2004, and Furfine, 2003, for

[1]For a thorough description of the financial crisis, see, e.g., Brunnermeier (2009).

[2]Bernanke (2009) and Rajan (2009) stress the danger induced by institutions which are "too interconnected to fail" or "too systemic to fail" in contrast to the insufficient focus on firms which are simply "too big too fail".

Germany and the U.S., respectively).[3] Furthermore, assessing risk interconnections on the basis of multivariate failure probability distributions has proven to be statistically complicated without using restrictive assumptions driving the results (see, e.g., Boss, Elsinger, Summer, and Thurner, 2004, or Zhou, 2009, and references therein). Finally, for regulators it is often unclear, how complex structures ultimately translate into dynamic and predictable measures of systemic relevance.

The objective of this paper is to develop an easily and widely applicable measure of a firm's systemic relevance, explicitly accounting for the company's interconnectedness within the financial sector. We assess companies' risk of financial distress on the basis of share price information which directly incorporates market perceptions of a firm's prospects, publicly accessible market data as well as balance sheet data. As for risk interconnectedness only dependencies in extreme tails of asset return distributions matter, we base our measure on extreme conditional quantiles of corresponding return distributions quantifying the risk of distress of individual companies and the entire system respectively. In this sense, our setting builds on the concept of conditional Value-at-Risk (VaR), which is a popular and widely accepted measure for tail risk.[4] For each firm, we identify its so-called *relevant (tail) risk drivers* as the minimal set of macroeconomic fundamentals, firm-specific characteristics and risk spillovers from competitors and other companies driving the company's VaR. Detecting with whom and how strongly any institution is connected allows us to construct a tail risk network of the financial system. A company's contribution to systemic risk is then defined as the induced total effect of an increase in its individual tail risk on the VaR of the entire system, conditional on the firm's position within the financial network as well as overall market conditions. Furthermore, by assessing a company's conditional VaR in dependence of respective tail risk drivers, we obtain a reliable measure of a company's idiosyncratic risk in the presence of network spillovers.

[3] See also Cocco, Gomes, and Martins (2009) for parts of the financial sector in Portugal, Elsinger, Lehar, and Summer (2006) for Austria, and Degryse and Nguyen (2007) for Belgium. A rare exception is the unique data set for India with full information on the intra-banking market studied in Iyer and Peydrió (2011).

[4] Note that the VaR is a coherent risk measure in realistic market settings, i.e., in cases of return distributions with tails decaying faster than those of the Cauchy distribution, see Garcia, Renault, and Tsafack (2007). In principle, our methodology could also be adapted to other tail risk measures such as, e.g., expected shortfall. Such a setting, however, would involve additional estimation steps and complications, probably inducing an overall loss of accuracy in results given the limited amount of available data.

The underlying statistical setting is a two-stage quantile regression approach: In the first step, firm-specific VaRs are estimated as functions of firm characteristics, macroeconomic state variables as well as tail risk spillovers of other banks which are captured by loss exceedances. Hereby, the major challenge is to shrink the high-dimensional set of possible cross-linkages between all financial firms to a feasible number of *relevant* risk connections. We address this issue statistically as a model selection problem in individual institution's VaR specifications which we solve in a pre-step. In particular, we make use of novel Least Absolute Shrinkage and Selection Operator (LASSO) techniques (see Belloni and Chernozhukov, 2011) which allows us to identify the relevant tail risk drivers for each company in a fully automatic way. The resulting identified risk interconnections are best represented in terms of a network graph as illustrated in Figure 1 (and discussed in more detail in the remainder of the paper) for the system of the 57 largest U.S. financial companies. In the second step, for measuring a firm's systemic impact, we individually regress the VaR of a value-weighted index of the financial sector on the firm's estimated VaR while controlling for the pre-identified company-specific risk drivers as well as macroeconomic state variables. We derive standard errors which explicitly account for estimation errors resulting from the pre-estimation of regressors in quantile relations. As the generally available sample sizes of balance sheet and macroeconomic information make the use of large-sample inference questionable, we provide (non-standard) bootstrap methods to construct finite-sample-based parameter tests.

We determine a company's systemic risk contribution as the marginal effect of its individual VaR on the VaR of the system. In analogy to an (inverted) asset pricing relationship in quantiles we call the measure *systemic risk beta*. It corresponds to the system's marginal risk exposure due to changes in the tail of a firm's loss distribution. For comparing the systemic relevance of companies across the system, however, it is necessary to compute the induced *total* increase in systemic risk. We therefore rank companies according to their "realized" systemic risk beta corresponding to the product of a company's systemic risk beta and its VaR. The systemic risk beta - and therefore also its realized version - is modeled as a function of firm-specific characteristics, such as leverage, maturity mismatch and size. Accordingly, a firm's tail risk effect on the system can vary with

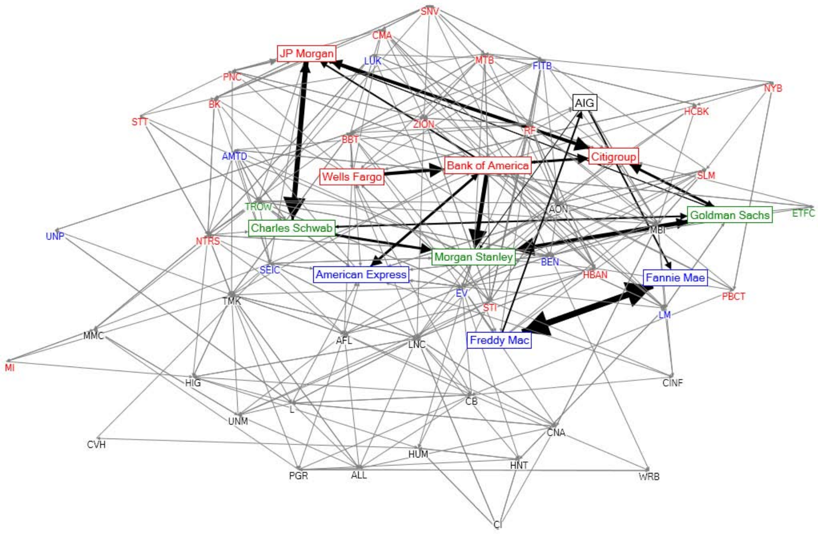

Figure 1: Risk network of the U.S. financial system schematically highlighting key companies in the system in 2000-2008. Details on all other firms in the system only appearing as unlabeled shaded nodes will be provided later in the paper. Depositories are marked in red, broker dealers in green, insurance companies in black, others in blue. An arrow pointing from firm j to firm i reflects an impact of extreme returns of j on the VaR of i (VaR^i) which is identified as being relevant employing statistical selection techniques presented in the remainder of the paper. VaRs are measured in terms of 5%-quantiles of the return distribution. The effect of j on i is measured in terms of the impact of an increase of the return X^j on VaR^i given X^i is below its 10% quantile, i.e., i's so-called loss exceedance. The size of the respective increase in VaR^j given a 1% increase of the loss exceedance of i is reflected by the thickness of the respective arrowhead where we distinguish between three categories: thin arrowheads display an increase up to 0.4, medium size of 0.4-0.8, and thick arrowheads of greater than 0.8. The thickness of the line of the arrow is chosen along the same categories. If arrows point in both directions, the thickness of the line corresponds to the bigger one of the two effects. The graph is constructed such that the total length of all arrows in the system is minimized. Accordingly, more interconnected firms are located in the center.

its economic conditions and/or its balance sheet structure changing its marginal systemic importance even though its individual risk level might be identical at different time points.

Our empirical results reveal a high degree of tail risk interconnectedness among U.S. financial institutions. In particular, we find that these network risk interconnection effects are the dominant risk drivers in individual risk. The detected channels of potential risk spillovers contain fundamental information for supervision authorities but also for company risk managers. Based on the topology of the systemic risk network, we can categorize firms into three broad groups according to their type and extent of connectedness with other companies: main risk transmitters, risk recipients and companies which both

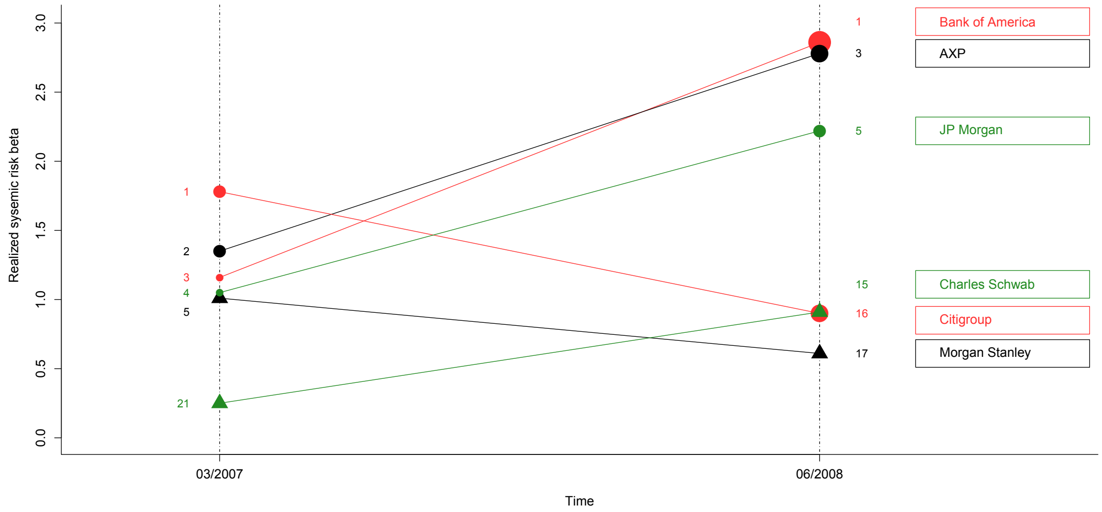

Figure 2: Systemic relevance of five exemplary firms in the U.S. financial system at two time points before and at the height of the financial crisis, 2008. Systemic relevance is measured in ”systemic risk betas” quantifying the marginal increase of the VaR of the system given an increase in a bank's VaR while controlling for the bank's (pre-identified) risk drivers. All VaRs are computed at the 5% level and are by definition positive. We depict respective "realized" versions of the systemic risk beta corresponding to the product of a risk beta and the corresponding VaR representing a company's total effect on systemic risk. Connecting lines are just added to graphically highlight changes between the two time points but do not mark real evolutions. The size of the elements in the graph reflects the size of the VaR of the respective company at each of the two time points. We use the following scale: the element is k·standard size with $k = 1$ for $VaR \leq 0.05$, $k = 1.5$ for $VaR \in (0.05, 0.1]$, $k = 2$ for $VaR \in (0.1, 0.15]$, $k = 3$ for $VaR \in (0.2, 0.25]$ and $k = 5.5$ for $VaR \in (0.65, 0.7]$. Attached numbers inside the figure mark the position of the respective company in an overall ranking of the 57 largest U.S. financial companies for each of the two time points.

receive and transmit tail risk. From a regulatory point of view, the second group of pure risk recipients has the least systemic impact. Monitoring their condition, however, might still convey important accumulated information on potentially hidden problems in those companies which act as their risk drivers. In any case, the internal risk management of these companies should account for the possible threat induced by the large degree of dependence on others. In particular, assessing their full risk exposure requires network augmented risk measures such as, e.g., our proposed VaR specifications depending on (pre-selected) network risk drivers. The highest attention of supervision authorities should be attracted by firms which mainly act as risk drivers or are highly interconnected risk transmitters in the system. These are particularly firms in the center of the network which appear as "too interconnected to fail", but also large risk producers at the boundary which are linked to only a few but heavily connected risk transmitters. While the systemic risk network yields *qualitative* information on risk channels and roles of companies within the financial system, estimates of systemic risk betas allow to *quantify* the resulting individual systemic relevance and thus complement the full picture. Ranking companies based on (realized) systemic risk betas shows that large depositories are particularly risky. After controlling for all relevant network effects, they have the overall strongest impact on systemic risk and should be regulated accordingly. Confirming general intuition, time evolutions of (realized) systemic risk betas indicate that most companies' systemic risk contribution sharply increases during the 2007/08 financial crisis. These effects are particularly pronounced for firms, which indeed got into financial distress during the crisis and are (ex post) identified as being clearly systemically risky by our approach. Figure 2 exemplarily illustrates the evolutions of their marginal systemic contributions – as reflected by systemic risk betas – as well as their exposure to idiosyncratic tail risk – as quantified by their VaR. A detailed pre-crisis case study confirms the validity of our methodology since firms such as, e.g., Lehman Brothers are ex-ante identified as being highly systemically relevant. It is well-known that their subsequent failure has indeed had a huge impact on the stability of the entire financial system. Likewise, the extensive bail-outs of American International Group (AIG), Freddie Mac and Fannie Mae can be justified given their high systemic risk betas and high interconnectedness by the end of 2007.

Our paper relates to several strands of recent empirical literature on systemic risk contributions. Closest to our work is White, Kim, and Manganelli (2010) who propose a bivariate vector-autoregressive system of each company's VaR and the system VaR. They capture time variations in tail risk in a pure time series setting which however does not account for mutual dependencies and network effects. In contrast, our set-up models tail risk in dependence of economic state variables and network spillovers which automatically account for periods of turbulence when predicting the systemic relevance. Building on VaR, Adrian and Brunnermeier (2011) were the first to construct a systemic risk measure, called $CoVaR$, with balance sheet characteristics driving individual risk exposures. Note that CoVaR is conceptionally different two our two-step quantile approach and can by definition only vary through the channel of individual risk of the considered company. Moreover, network interconnections are not addressed which we identify as crucial for the performance of the model. Our work also complements papers which measure a company's systemic relevance by focusing on the size of potential bail-out costs, such as Acharya, Pedersen, Philippon, and Richardson (2010) and Brownlees and Engle (2011). Such approaches cannot detect spillover effects driven by the topology of the risk network and might under-estimate the systemic importance of small but very interconnected companies. Moreover, while Brownlees and Engle (2011) study the situation of an individual firm given that the system is under distress, we investigate the reverse relation and measure the effect on the system given an individual firm is in financial trouble. Both approaches are justified as they take complementary perspectives and measure different dimensions of systemic risk. In the same way, we also complement macroeconomic approaches taking a more aggregated view as, e.g., the literature on systemic risk indicators (e.g., Segoviano and Goodhart, 2009, Giesecke and Kim, 2011) or papers on early warning signals (e.g., Schwaab, Koopman, and Lucas, 2011, and Koopman, Lucas, and Schwaab, 2011).

The remainder of the paper is structured as follows. In Section 1, we briefly explain the modeling idea and describe the underlying data. Section 2 presents the model and estimation procedure for individual companies' VaRs, before discussing results on the financial network structure. Section 3 gives the second stage, the system VaR model, including estimation procedure, inference method and empirical results. In Section 4, we robustify and validate our results by presenting a case study of five large financial institutions that were affected by the financial crisis, and try to predict their distress and systemic relevance using only pre-crisis data. Section 5 concludes.

1 Measuring Systemic Relevance in a Network

1.1 Framework

Assessing and predicting dependence between systemic risk and firm-specific risk requires modeling regression relations in the (left) tails of respective asset return distributions, rather than in the center. This is in sharp contrast to a standard correlation analysis in (conditional) means which cannot quantify spillovers in tail situations of financial distress, and also goes beyond simple descriptive correlations between tails. Tail correlations do not allow detecting causal dependencies between tails and do not permit forecasting systemic risk contributions. We consider a stress-test-type scenario for assessing how changes in individual company-specific risk affect the risk of failure of the entire system given underlying network dependencies between institutions and market externalities at the respective point in time. Therefore, our model does not feature a general equilibrium framework, but is exclusively designed to provide a practically feasible and reliable measure of a company's marginal contribution to systemic risk in the presence of risk spillovers from other companies. These underlying network linkages between tail risks of firms in the system must be identified in a first step.

Defining the company-specific asset return as X_t^i, we measure the tail risk of a company as its conditional Value-at-Risk (VaR), $VaR_{p,t}^i$, given a set of company-specific *tail risk drivers* $\mathbf{W}_t^{(i)}$ containing network influences from other institutions in the system, i.e.,

$$\Pr(-X_t^i \geq VaR_{p,t}^i | \mathbf{W}_t^{(i)}) = \Pr(X_t^i \leq Q_{p,t}^i | \mathbf{W}_t^{(i)}) = p \tag{1}$$

with $VaR_{p,t}^i = VaR_{p,t}^i(\mathbf{W}_t^{(i)}) = -Q_{p,t}^i$ denoting the (negative) conditional p-quantile of X_t^i.[5] Likewise, system risk, $VaR_{p,t}^s$, is measured as the conditional VaR of the system return X_t^s obtained as the value-weighted average return of the set of all major financial companies.[6] To measure the systemic impact of company i, the system VaR is modeled in dependence of $VaR_{p,t}^i$ and additional control variables $\mathbf{V}_t$, i.e., $VaR_{p,t}^s = VaR_{p,t}^s(VaR_{p,t}^i, \mathbf{V}_t) = -Q_{p,t}^s$. Then, we define the *systemic risk beta* as the marginal effect of firm i's tail risk on the system tail risk given by

$$\frac{\partial VaR_{p,t}^s(\mathbf{V}_t, VaR_{q,t}^i)}{\partial VaR_{q,t}^i} = \beta_{p,q}^{s|i}. \tag{2}$$

We classify the systemic relevance of institutions according to the statistical significance of $\beta_{p,q}^{s|i}$ and the size of their total effect $\beta_{p,q}^{s|i} VaR_{q,t}^i$. We define the latter as a firm's *realized systemic risk contribution* raising with the system's marginal exposure to the company's

[5] Defining VaR as the *negative* p-quantile ensures that the Value-at-Risk is positive and is interpreted as a loss position.

[6] For details, see Section 1.2.

tail risk (measured by $\beta_{p,q}^{s|i}$) and the firm's $VaR_{q,t}^{i}$. Changes in systemic relevance over time, however, cannot only occur through $VaR_{q,t}^{i}$ but also through the systemic risk beta $\beta_{p,q}^{s|i}$ which we allow to vary in firm-specific characteristics (see Section 3).[7] Note that this is conceptionally different to CoVaR of Adrian and Brunnermeier (2011).

As the VaR is not observable and has to be estimated, a major challenge is to select appropriate significant conditioning variables $\mathbf{W}_t^{(i)}$ yielding a flexible but still parsimonious model specification. We determine the *relevant* i-specific tail risk drivers out of a large set of potential regressors $\mathbf{W}_t$ containing lagged macroeconomic state variables $\mathbf{M}_{t-1}$, lagged firm-specific characteristics $\mathbf{C}_{t-1}^{i}$, the i-specific lagged return X_{t-1}^{i}, and influences of all other companies apart from i, $\mathbf{E}_t^{-i} = (E_t^j)_{j\neq i}$, by a statistical selection technique as discussed in the remainder of the paper. We find that these intra-system influences are best captured via contemporaneous loss exceedances, where the loss exceedance of a firm j is defined as $E_t^j = X_t^j 1(X_t^j \leq \hat{Q}_{0.1}^j)$ and $\hat{Q}_{0.1}$ is the unconditional 10% sample quantile of X^j. Hence, company j only affects the VaR of company i if the former is under pressure. Since $\mathbf{E}_t^{-i}$ are return *realizations* and VaR_t^i is a future predicted quantity, this specification furthermore circumvents simultaneity issues. A model for VaR_t^i based on economic state variables as well as loss exceedances by construction automatically adjusts and prevails in distress scenarios under shocks in externalities. This is a clear advantage compared to pure time series approaches (cp. e.g. White, Kim, and Manganelli, 2010, and Brownlees and Engle, 2010).

The selection step allows identifying which (and how strongly) loss exceedances of other companies influence $VaR_{p,t}^{i}$ and is crucial for accounting for network dependencies between companies. As demonstrated in the sequel of the paper, the latter are crucial for appropriately explaining individual tail risks. Moreover, identifying cross-firm dependencies for each company i is not only essential for appropriately capturing firm-specific VaRs in a first step but is also crucial for selecting necessary control variables in the estimation of $\beta_{p,q}^{s|i}$ in the second step. In particular, for an unbiased estimate of $\beta_{p,q}^{s|i}$, it is necessary to control for any tail risk drivers influencing *both* $VaR_{p,t}^{s}$ and VaR_{q}^{i}. Accordingly, $\mathbf{V}_t$ must contain macroeconomic state variables as well as the tail risks (represented

[7]For ease of illustration, here we skip the time index in $\beta_{p,q}^{s|i}$.

by the VaRs) of *all* companies which are identified to influence company i. Ignoring these spillover effects would lead to a biased measure of systemic risk contribution.

The identified risk connections between all firms constitute a systemic risk network. The latter is not only a prerequisite for the quantification of marginal systemic risk contributions but contains additional valuable regulatory information on potential risk channels and specific roles of companies as risk transmitters and/or recipients. Accordingly, the following analysis consists of two steps where in the first step firm-specific VaRs and network effects are quantified (Section 2) before in the second step, systemic risk betas are estimated while controlling for the (pre-)identified cross-company dependencies (Section 3).

1.2 Data

Our analysis focuses on publicly traded U.S. financial institutions. The list of included companies in Table 1 (see Appendix B) comprises depositories, broker dealers, insurance companies and Others.[8] To assess a firm's systemic relevance, we use publicly available market and balance sheet data. Such data constitutes a solid basis for transparent regulation since timely access on detailed information of connections between firms' assets and obligations, is very difficult and expensive to obtain – even for central banks.

Daily equity prices are obtained from Datastream and are converted to weekly log returns. To account for the general state of the economy, we use weekly observations of seven lagged macroeconomic variables $\boldsymbol{M}_{t-1}$ as suggested and used by Adrian and Brunnermeier (2011) (abbreviations as used in the remainder of the paper are given in brackets): the implied volatility index, VIX, as computed by the Chicago Board Options Exchange (vix), a short term "liquidity spread", computed as the difference of the 3-month collateral repo rate (available on Bloomberg) and the 3-month Treasury bill rate from the Federal Reserve Bank of New York (repo), the change in the 3-month Treasury bill rate (yield3m) and the change in the slope of the yield curve, corresponding to the spread between the 10-year and 3-month Treasury bill rate (term). Moreover, we utilize

[8]Companies are distinguished according to their two-digit SIC codes, following the categorization in Acharya, Pedersen, Philippon, and Richardson (2010).

the change in the credit spread between BAA rated bonds and the Treasury bill rate (both at 10 year maturity) (credit), the weekly equity market return from CRSP (marketret) and the one-year cumulative real estate sector return, computed as the value-weighted average of real estate companies available in the CRSP data base (housing).

Moreover, to capture characteristics of individual institutions predicting a bank's propensity to become financially distressed, $\boldsymbol{C}_{t-1}^{i}$, we follow Adrian and Brunnermeier (2011) and use (i) leverage, calculated as the value of total assets divided by total equity (in book values) (LEV), (ii) maturity mismatch, measuring short-term refinancing risk, calculated as short term debt net of cash divided by the total liabilities (MMM), (iii) the market-to-book value, defined as the ratio of the market value to the book value of total equity (BM), (iv) market capitalization, defined by the logarithm of market valued total assets (SIZE) and (v) the equity return volatility, computed from daily equity return data (VOL). The system return is chosen as the return on the financial sector index provided by Datastream. It is computed as the value-weighted average of prices of 190 U.S. financial institutions.

As balance sheets are available only on a quarterly basis, we interpolate the quarterly data to a daily level using cubic splines, and then aggregate them back to calendar weeks. We focus on 57 financial institutions existing through the period from beginning of 2000 to end of 2008, resulting into 467 weekly observations on individual returns. This restriction has the drawback of excluding companies which defaulted during the financial crisis. Therefore, to address this issue and to validate and robustify our approach, we re-estimate the model over a sub-period ending before the financial crisis and including, among others, the investment banks Lehman Brothers and Merrill Lynch that were massively affected by the crisis.

2 A Tail Risk Network

2.1 Measuring Firm-Specific Tail Risks

2.1.1 Identification of Tail Risk Drivers

Specifying the VaR of firm i at time point $t = 1, \dots, T$ as a linear function of the i-specific tail risk drivers $\mathbf{W}_t^{(i)}$,

$$VaR_q^i = \mathbf{W}^{(i)\prime} \boldsymbol{\xi}_q^i \ , \tag{3}$$

yields a linear function in return quantiles

$$X_t^i = -\mathbf{W}_t^{(i)\prime} \boldsymbol{\xi}_q^i + \varepsilon_t^i, \quad \text{with} \quad Q_q(\varepsilon_t^i | \mathbf{W}_t^{(i)}) = 0. \tag{4}$$

If we knew the i-relevant risk drivers $\mathbf{W}^{(i)}$ selected out of $\mathbf{W}$, then, estimates $\widehat{\boldsymbol{\xi}_q^i}$ of $\boldsymbol{\xi}_q^i$ could be obtained according to standard linear quantile regression (Koenker and Bassett, 1978) by minimizing

$$\frac{1}{T} \sum_{t=1}^{T} \rho_q \left(X_t^i + \mathbf{W}_t^{(i)\prime} \boldsymbol{\xi}_q^i \right) \tag{5}$$

with loss function $\rho_q(u) = u(q - I(u < 0))$, where the indicator $I(\cdot)$ is 1 for $u < 0$ and zero otherwise, and

$$\widehat{VaR}_{q,t}^i = \mathbf{W}_t^{(i)\prime} \widehat{\boldsymbol{\xi}}_q^i \ . \tag{6}$$

However, the relevant risk drivers $\mathbf{W}^{(i)}$ for firm i are unknown and must be determined from $\mathbf{W}$ in advance. Model selection is not straightforward in the given setting as tests on the individual significance of single variables do not account for the (possibly high) collinearity between the covariates. Moreover, sequences of joint significance tests have too many possible variations to be easily checked in case of more than 60 variables. Since alternative model selection criteria, like the Bayes Information Criterion (BIC) or the Akaike Information Criterion (AIC), are not available in a quantile setting, we choose the *relevant* covariates in a data-driven way by employing a statistical shrinkage technique known as the least absolute shrinkage and selection operator (LASSO). LASSO methods are standard for high-dimensional conditional mean regression problems (see Tibshirani, 1996), and have recently been adapted to quantile regression by Belloni and Chernozhukov (2011). Accordingly, we run an l_1-penalized quantile regression and calculate for a fixed individual penalty parameter λ^i,

$$\widetilde{\boldsymbol{\xi}}^i_q = \text{argmin}_{\boldsymbol{\xi}^i} \frac{1}{T} \sum_{t=1}^{T} \rho_q \left(X^i_t + \mathbf{W}'_t \boldsymbol{\xi}^i \right) + \lambda^i \frac{\sqrt{q(1-q)}}{T} \sum_{k=1}^{K} \hat{\sigma}_k |\xi^i_k| \;, \tag{7}$$

with the set of potentially relevant regressors $\mathbf{W}_t = (W_{t,k})_{k=1}^K$, componentwise variation $\hat{\sigma}^2_k = \frac{1}{T}\sum_{t=1}^{T}(W_{t,k})^2$ and the loss function ρ_q as in (5). The key idea is to select relevant regressors according to the absolute value of their respective estimated marginal effects (scaled by the regressor's variation) in the penalized VaR regression (7). Regressors are eliminated if their shrunken coefficients are sufficiently close to zero. Here, all firms in $\mathbf{W}$ with absolute marginal effects $|\widetilde{\boldsymbol{\xi}}^i|$ below a threshold $\tau = 0.0001$ are excluded keeping only the $K(i)$ remaining relevant regressors $\mathbf{W}^{(i)}$. Hence, LASSO de-selects those regressors contributing only little variation. Due to the additional penalty term in (7), all coefficients $\widetilde{\boldsymbol{\xi}}^i_q$ are generally downward biased in finite samples. Therefore, we re-estimate the unrestricted model (5) only with the selected relevant regressors $\mathbf{W}^{(i)}$ yielding the final estimates $\widehat{\boldsymbol{\xi}}^i_q$. This post-LASSO step produces finite sample estimates of coefficients $\boldsymbol{\xi}^i_q$ which are superior to the original LASSO estimates or plain quantile regression results without penalization suffering from overidentification problems (see the original paper by Belloni and Chernozhukov (2011) for consistency of the post LASSO step).

The selection of relevant risk drivers via LASSO crucially depends on the choice of the company-specific penalty parameter λ^i. The larger λ^i, the more regressors are eliminated. Conversely, in case of $\lambda^i = 0$, we are back in the standard quantile regression setting (5) without any de-selection. For each institution, we determine the appropriate penalty level λ^i in a completely data-driven way such that it dominates a relevant measure of noise in the sample criterion function. In particular, we use the supremum norm of a suitably rescaled gradient of the sample criterion function evaluated at the true parameter value as in Belloni and Chernozhukov (2011). In this sense, number and elements of the set of relevant risk drivers are determined only from the data without any restrictive pre-assumptions. For details on the empirical procedure we refer to Appendix A.2.

Evaluating the goodness of fit of conditional VaR model specifications should take into account how well the model captures the specific percentile of the return distribution but also how well the model predicts size and frequency of losses. The latter issue cannot be captured, e.g., by quantile-based modifications of the conventional R^2. We therefore consider a VaR specification as inadequate if it either fails producing the correct empirical level of VaR exceedances but also if the sequence of exceedances is *not* independently and identically distributed over the considered time period. This proceeding ensures that VaR violations today do not contain information about VaR violations in the future and both occur according to the same distribution. This is formally tested using a likelihood ratio (LR) version of the dynamic quantile (DQ) test developed in Engle and Manganelli (2004) and described in detail in Appendix A.3. Berkowitz, Christoffersen, and Pelletier (2009) show that this likelihood ratio (LR) test has superior size and power properties compared to competing conditional VaR backtesting methods which dominate plain unconditional level tests (as e.g. Kupiec (1995)).

2.1.2 Empirical Evidence

We estimate VaR specifications with q=0.05 for all companies employing the LASSO selection procedure described in Section 2.1.1.[9] Exemplary VaR^i (post-)LASSO regression results for firms in the four industrial sectors depositories, insurances, brokers and others are provided in Table 2.

The main drivers of company-specific VaRs are loss exceedances of other firms. In their presence, macroeconomic variables and firm-specific characteristics often do not have any statistically significant influence and are not selected by the LASSO procedure. In Table 2, only for Torchmark (TMK) and Regions Financial (RF) regressors other than cross-firm links are selected. In contrast, VaR specifications of Goldman Sachs (GS), Morgan Stanley (MS), JP Morgan (JPM) and AIG exclusively contain loss exceedances

[9]Due to the limited number of observations, we refrain from considering more extreme probabilities.

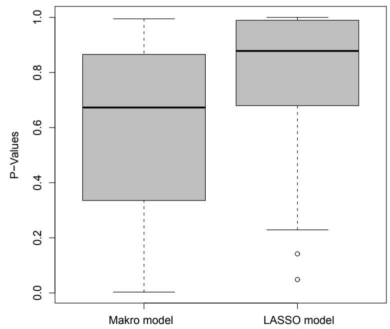

Figure 3: Boxplots of backtesting p-values indicating the in-sample model fit of VaR specifications including macroeconomic regressors only (left) and VaR specifications resulting from the LASSO selection procedure (7) (right).

from other firms. Particularly the connections between close competitors, such as Goldman Sachs and Morgan Stanley and the influence of mortgage company Freddie Mac (FRE) on AIG correspond are highly plausible and are confirmed by market evidence. The relevance of cross-firm effects is additionally robustified by testing for the joint significance of the individually selected loss exceedances $\mathbf{E}_t^{-i}$. This is performed based on a quantile regression version of the F-test of linear hypothesis developed by Koenker and Bassett (1982). We find that the selected tail risk spillovers are highly significant in all but very few cases. See Table 3 for an overview of all cross-effects.

The importance of including other companies' loss exceedances as potential risk drivers for a company i is also illustrated by a simple comparison of the forecast performance of our LASSO-selected specifications to a model of VaR^i only using macroeconomic variables as in Adrian and Brunnermeier (2011). According to the employed backtests, specifications allowing for cross-firm dependencies reveal a strong predictive ability and are significantly superior to simplistic models including macroeconomic regressors only. Figure 3 shows the distributions of the backtesting p-values implied by both models. Hence, inter-company linkages do not only add crucial explanatory power in VaR specifications but in fact contain the main information for explaining individual tail risk.

Our results show that the major information about cross-company dependencies in tail risks is primarily contained in *contemporaneous* loss exceedances $\mathbf{E}_t^{-i}$. In contrast, alternative VaR specifications utilizing corresponding returns X_t^{-j} or lagged loss exceedances

$\mathbf{E}_{t-1}^{-i}$ imply significantly inferior backtest performances with the regressors being mostly not significant in joint F-tests.[10] Moreover, linking VaR forecasts and thus predictions of *hypothetical* losses to already *realized* loss exceedances allows measuring mutual dependencies between companies without requiring a simultaneous system of equations in conditional quantiles. In particular, observed bi-directional relationships between conditional quantiles and realized loss exceedances of different firms (e.g., between Goldman Sachs and Morgan Stanley) do not reflect simultaneities as feedbacks are not contemporaneous: For instance, a highly negative (realized) return of company j increases the conditional loss quantile and therefore increases the VaR of firm i. However, a higher conditional VaR of i does not necessarily directly increase the absolute realized loss return of i but just makes it more likely. Avoiding an explicit treatment of simultaneities in quantiles while still addressing network dependencies is an important advantage of our approach.[11]

2.2 Network Model and Structure

We constitute a tail risk network of the system from individually selected loss exceedances reflecting cross-firm dependencies. Taking all firms as nodes in such a network, there is an influence of firm j on firm i, if E^j is LASSO-selected in (7) as a relevant risk externality of firm i in VaR_q^i. In particular, if E^j is part of $\mathbf{W}^{(i)}$ as its k-th component, then the corresponding coefficient $\xi_{q,k}^i$ in $\boldsymbol{\xi}_q^i$ marks the risk impact of firm j on firm i in the network. If E^j is not selected as relevant risk driver of firm i, there is no arrow from firm j to firm i.

For each company in the system, the network builds on only directly influencing and influenced firms and all other companies directly influencing the influenced firms. In the Bayesian network literature, these constitute a so-called Markov blanket assumed to contain all relevant information for predicting the node's role in the network (see Friedman,

[10] All F-test results are available upon request and omitted here for sake of brevity.

[11] Econometrically it is open how to handle such a system in conditional quantiles in general. In contrast to relations in (conditional) means, it is unclear how marginal q-quantiles constitute the respective quantile in the joint distribution under appropriate independence assumptions. Only in lags, restricted to very small dimensions and under strong assumptions, solutions have been obtained via CaViAR type recursions (see White, Kim, and Manganelli (2010)).

Geiger, and Goldszmidt, 1997). An overview of the identified tail risk connections between all companies is provided in Table 3 reporting which company's loss exceedance affects which others' VaR and vice versa. We observe that the number of risk connections substantially varies over the cross-section of companies. While some firms such as, e.g. , Morgan Stanley, Bank of America (BAC), American Express (AXP) as well as Bank of New York Mellon (BK), are strongly inter-connected with many other companies, there are institutions, such as Fannie Mae (FNM), AIG (AIG) and a couple of further insurances revealing significantly less cross-firm dependencies. In order to effectively illustrate identified risk connections and directions, we graphically depict the resulting network of companies in Figure 5. The layout and allocation of the network is chosen such that the sum of cross-firm distances are minimized. Consequently, the most connected firms are located in the center of the network while the less involved companies are placed at its boundary.

The resulting network topology reveals different roles of companies within the financial network. We distinguish between three major categories: The first group contains companies with only few incoming arrows but numerous outgoing ones and thus mainly act as risk drivers within the system. These are institutions whose potential failure might affect many others but, conversely, which are themselves relatively unaffected by the distress of other firms. Risk management of such firms can therefore be based mostly on idiosyncratic criteria without accounting too much for influences of the system. For regulatory authorities, however, a close monitoring is important as a failure of such a company can induce substantial systemic risks through multiple channels into the financial network. Our results show that only few firms belong to this category. Examples are State Street Corporation (STT), one of the top ten U.S. banks, Leucadia National Corporation (LUK), a holding company which is, among others, engaged in banking, lending and real estate, and SEI Investments Company (SEIC), a financial services firm providing products and service in asset and investment management. Financial distress of these banks obviously has wide-spread consequences. For instance, State Street reveals spillovers to the financial services companies American Express and Northern Trust (NTRS), the Bank of New York Mellon and Morgan Stanley. Leucadia affects Citigroup (C), one of the biggest banks in the U.S., and Freddie Mac, one of the two largest U.S. mortgage companies.

Finally, SEI Investments has links to various big institutions, such as Bank of America, American Express, Morgan Stanley and the online broker TD Ameritrade (AMTD).

The second group contains companies which mainly are risk takers within the system. These companies are not necessarily systemically risky but might severely suffer from distress of others and should account for such spillovers in their internal risk management. According to Table 3 and Figure 5 these firms are primarily insurance companies. Examples are Cincinnati Financial Corporation (CINF), a company for property and casualty insurance, Humana Incorporation (HUM) managing health insurances or Progressive Corporation Ohio (PGR) providing automobile insurance and other property-casualty insurances.

The third group is the largest category within the network. It consists of companies which serve as both risk recipients and risk transmitters which amplify tail risk spillovers by further disseminating risk into new channels. Due to their role as risk distributors such companies are key systemic players and should be supervised accordingly. We further distinguish between strongly and less connected firms. The first subgroup is the most difficult but most important to regulate tightly. Examples are Goldman Sachs, Citigroup, Morgan Stanley, AON Corporation (AON), Bank of America, American Express, Freddie Mac as well as the insurance company MBIA (MBI), among many others. Bank of America and Citigroup are among the five largest banks in the U.S. and reveal strong connections to various other big institutions, such as Morgan Stanley, JP Morgan, Goldman Sachs, American Express, Regions Financial and AIG. Details on the specific role of Citigroup and Morgan Stanley within the system are highlighted in Figure 6. Morgan Stanley, with strong links to many companies, such as Goldman Sachs, Bank of America and the savings bank Hudson City Bancorporation (HCBK), and the insurance company AON are examples for deeply connected firms located in the center of the network. Likewise, Freddie Mac is strongly involved and was particularly affected by the 2008 credit crunch in the mortgage sector. Accordingly, also MBIA realized severe losses during the financial crisis due to investments in mortgage backed securities.
The second subgroup might be technically easier to monitor with companies revealing risk connections with only very few other firms. Still, supervision is not less important

than for the first subgroup. Examples are Fannie Mae and AIG. Fannie Mae reveals significant bilateral risk connections to its main competitor Freddie Mac. AIG holds significant positions in mortgage backed securities and as a consequence is closely connected to both Fannie Mae and Freddie Mac. Probably due to the same reason, we also observe bilateral tail risk dependencies between AIG and MBIA. Even though their number of relevant risk connections within the network is limited, such firms can still have a crucial overall impact on the system. In case of the 2008 financial crisis, the dependence between Freddie Mac and Fannie Mae as well as their interaction with AIG had severe systemic consequences.

Figure 7 reveals that it is not sufficient to focus on sector-specific subnetworks only. Indeed interconnectedness of institutions occurs to a large proportion *between* industrial sectors. In these circle layout network graphs, companies are grouped according to industries with risk outflows for each group being highlighted. We observe that tail risks of depositories, insurances and others are relatively equally distributed among all other industry groups. Depositories are most strongly connected and also reveal the strongest tail risk links among each other. This is in contrast to the other industries where cross-firm connections *within* a group are less strong. Moreover, in contrast to other industry categories, the risk outflow of broker dealers is clearly more concentrated. They particularly affect big banks such as Bank of America and Citigroup as well as financial service companies such as American Express or SEI. Only very few direct connections to insurance companies are revealed.

Besides graphical illustration and inflow-outflow categorizations, standard network characteristics can provide a more comprehensive picture of the interconnectedness and the role of each node in the system. In Figure 4 we depict firms' pagerank coefficient (see Brin and Page (1998)) which does not plainly count links but empirically weights their importance in an iterative scheme.[12] Confirming the visual impression based on Figure 5, the most connected firms are Lincoln National Corporation, AON, Bank of America,

[12]The key idea is to assign a weight to each node (i.e., a company in our context) which is increasing with the number of connections to others and the relative importance thereof. The more connected a firm is, the higher its importance and thus the higher the importance of its neighbor. The computation of the pagerank coefficient can be understood as an eigenvalue problem which can solved iteratively. For more details, see Berkhin (2005).

TD Ameritrade and Morgan Stanley. The graph confirms our finding above that depositories tend to be slightly stronger involved than the other industry groups. Particularly insurances reflect a separation into a group of highly connected firms, such as Lincoln National Corp., AON and MBI, and a group of companies being less connected, such as AIG, Humana Incorp. , Unum Group (UNM) and Cincinnati Financial Corp.

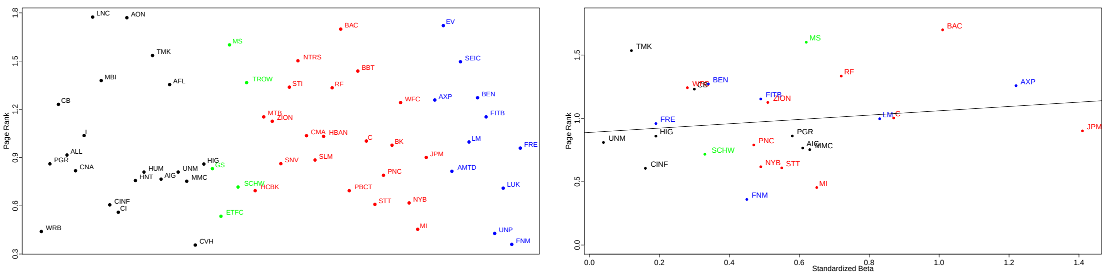

Figure 4: The left figure displays pagerank coefficients based on the estimated tail risk network computed as in Berkhin (2005) with ordering of institutions according to sectors. On the right, pagerank coefficients are plotted versus realized systemic risk contributions for all companies which are classified as systemically relevant for the years 2000-2008 as in Subsection 3.3. The solid regression line shows only a small correlation between the pagerank coefficent and the realized beta, supported by the respective R^2 of 0.0265 of the regression. Colors and acronyms are as in Figure 7 above.

Note that pagerank coefficients such as other network metrics can only assess the local impact and centrality of firms in the network containing relevant but not all information for judging overall systemic relevance. Therefore, a risk network does not allow to fully quantitatively assess the systemic relevance of a financial institution. Nevertheless, the degree of firms' interconnectedness and the specific topology of the network or corresponding sub-networks allows to identify possible risk channels in the system. These interlinkages are central but not comprehensive for macroprudential regulation reflecting the particular role of a firm as risk recipient, transmitter or distributor of tail risk. To explicitly *quantify* a firm's marginal systemic relevance, we propose the concept of systemic risk betas presented in the following section.

3 Quantifying Systemic Risk Contributions

3.1 Measuring Systemic Risk Betas

Besides valuable information on financial network structures, the focus of supervision authorities is on an accurate but parsimonious measure of an institutions' systemic impact. We quantify the latter as the effect of a marginal change in the tail risk of firm i on the tail risk of the system given the underlying network structure of the financial system. In order to obtain unbiased estimates of this specific marginal effect in the VaR regression of the system, however, it is sufficient to additionally only control for firms which are relevant i-specific risk drivers in the network. Conversely, variables unrelated to VaR^i do not affect firm i's systemic risk contribution.[13] Thus, a fully-fledged structural general equilibrium model is not necessary. Even if correctly specified, an equilibrium setting would be practically infeasible failing to deliver sufficiently precise estimates given the high-dimensionality and interconnectedness of the financial system on the one hand and the limited data availability on the other.

For this reason, we propose estimating systemic risk contributions based on models which are specific for each firm i as they only control for the i-specific risk drivers. Correspondingly, we estimate the firm-i-specific *systemic risk beta* $\beta^{s|i}_{q,p}$ based on a linear model for the system VaR of the form

$$VaR^s_{p,t} = \mathbf{V}_t^{(i)\prime}\gamma^s_p + \beta^{s|i}_{p,q} VaR^i_{q,t}, \tag{8}$$

where the vector of regressors $\mathbf{V}_t^{(i)} = (1, \mathbf{M}_{t-1}, \mathbf{VaR}^{(-i)}_{q,t})$ includes a constant effect, lagged macroeconomic state variables and the VaRs of all companies which are identified as risk drivers for firm i via LASSO in Section 2.

The systemic risk beta $\beta^{s|i}_{p,q} = \beta^{s|i}$ of company i captures the effect of a marginal change in VaR^i_t on VaR^s_t. It can be interpreted in analogy to an inverse asset pricing relationship in quantiles, where bank i's q-th return quantile drives the p-th quantile of the

[13]See Angrist, Chernozhukov, and Fernández-Val (2006) for a simple Frisch-Waugh-type argument in quantile regressions.

system given network-specific effects and firm-specific and macroeconomic state variables.[14] Accordingly,

$$\bar{\beta}^{s|i}_{p,q} := \beta^{s|i}_{p,q} VaR^i_t \tag{9}$$

measures the full partial effect of a tail risk increase of bank i on VaR^s_t. We refer to $\bar{\beta}^{s|i}_{p,q}$ as the *realized* systemic risk contribution as it is is computed based on market realizations and is useful for real-time crisis monitoring. Moreover, scaling systemic risk betas by the corresponding VaR allows to cross-sectionally compare systemic risk contributions and to rank banks according to their systemic relevance.

During periods of turbulence, not only banks' risk exposures change but also their marginal importance for the system might vary. We therefore allow $\beta^{s|i}$ being time-varying. In particular, time-variation occurs through observable factors $\mathbf{Z}^i$ characterizing a bank's propensity to get in financial distress. Accordingly, $\beta^{s|i}_t$ should be interpreted as a *conditional* systemic risk beta. Basing $\beta^{s|i}$ on lagged characteristics, makes betas and thus corresponding systemic risk rankings predictable which is important for forward-looking regulation. To limit complexity and computational burden of the model, we assume linearity of $\beta^{s|i}_{p,q,t}$ in firm-specific distress indicators $\mathbf{Z}^i_{t-1}$,

$$\beta^{s|i}_{p,q,t} = \beta^{s|i}_{0,p,q} + \mathbf{Z}^{i\,\prime}_{t-1} \boldsymbol{\eta}^{s|i}_{p,q}, \tag{10}$$

where $\boldsymbol{\eta}^{s|i}_{p,q}$ are the parameters driving the time-varying effects. The case of a constant systemic risk beta is obviously contained as a special case if $\boldsymbol{\eta}^{s|i}_{p,q} = 0$ and thus $\beta^{s|i}_{0,p,q} = \beta^{s|i}_{p,q,t} = \beta^{s|i}_{p,q}$.

We choose $\mathbf{Z}^i_t = C^i_t$ as the firm-specific tail risk drivers since size, leverage, maturity mismatch, book-to-market ratio and volatility might not only affect a bank's VaR, but also directly drive its marginal systemic relevance. As a consequence, systemic risk contributions of two companies with the same exposure to macroeconomic risk factors and financial network spillovers may be still different as they depend on their balance sheet

[14]Note that our stress test scenario only studies the immediate effect of an exogenous risk shock in company i for the system. We do not infer anything about further steps which should then also account for converse effects of increases of system risk causing firm specific risk to raise.

structures. The significance of time variation in these quantities can then be statistically tested for (see Subsection 3.3 below).

Due to the linearity of (10) we can thus write the quantile model (8) for VaR_p^s with time-varying $\beta_{p,q,t}^{s|i}$ in the following form

$$VaR_{p,t}^s = \mathbf{V}_t^{(i)\prime}\boldsymbol{\gamma}_p^s + \beta_{0,p,q}^{s|i} VaR_{q,t}^i + (VaR_{q,t}^i \cdot \mathbf{Z}_{t-1}^i)' \boldsymbol{\eta}_{p,q}^{s|i} \, . \tag{11}$$

3.2 Estimation and Inference

If firm specific VaRs were directly observable, the magnitude and significance of i-specific systemic risk betas could be directly inferred from the linear quantile regression (11) in analogy to (5) with the VaR defined by (1). However, note that the regressors VaR_t^i and $\mathbf{VaR}_{q,t}^{(-i)}$ in $\mathbf{V}^{(i)}$ are pre-estimated as they arise from the first-step quantile regressions as shown in Section 2. Hence, operationalizing (11) with $\widehat{VaR}_t^i$ and $\widehat{\mathbf{VaR}}_{q,t}^{(-i)}$ as generated regressors, yields the (second step) quantile regression,

$$\begin{aligned} X_t^s &= -\widehat{\mathbf{V}^{(i)}}_t'\boldsymbol{\gamma}_p^s - \beta_{0,p,q}^{s|i}\widehat{VaR}_{q,t}^i - (\widehat{VaR}_{q,t}^i \cdot \mathbf{Z}_{t-1}^i)'\boldsymbol{\eta}_{p,q}^{s|i} + \varepsilon_t^s, \\ &\text{with} \quad Q_p(\varepsilon_t^s | \widehat{VaR}_{q,t}^i, \widehat{\mathbf{V}}_t^{(i)}, \mathbf{Z}_{t-1}^i) = 0 \, . \end{aligned} \tag{12}$$

With the notation $\widehat{\mathbf{V}}^{(i)}$, we stress that some components of $\mathbf{V}^{(i)}$ are pre-estimated as $\widehat{\mathbf{VaR}}_q^{(-i)}$. Then, analogously to the first-step regressions in Section 2, parameter estimates are obtained via quantile regression minimizing

$$\frac{1}{T}\sum_{t=1}^{T}\rho_p\left(X_t^s + \widehat{\mathbf{V}^{(i)}}_t'\boldsymbol{\gamma}_p^s + \beta_{0,p,q}^{s|i}\widehat{VaR}_{q,t}^i + (\widehat{VaR}_{q,t}^i \cdot \mathbf{Z}_{t-1}^i)'\boldsymbol{\eta}_{p,q}^{s|i}\right) \tag{13}$$

in the unknown parameters. Consequently, the resulting estimate of the full time-varying marginal effect $\widehat{\beta}_{p,q}^{s|i}$ in (10) is obtained as

$$\widehat{\beta}_{p,q,t}^{s|i} = \widehat{\beta}_{0,p,q}^{s|i} + \mathbf{Z}_{t-1}^{i}{}'\widehat{\boldsymbol{\eta}_{p,q}^{s|i}} \tag{14}$$

for given values $\mathbf{Z}_{t-1}^i$.

Since $VaR^i_{q,t}$ is a function of $\mathbf{W}^{(i)}$, conditional quantile independence in (12) is equivalent to $Q_p(\varepsilon^s_t|\mathbf{W}^{(i)}_t, \mathbf{W}^{(-i)}_t, \mathbf{Z}^i_{t-1}) = 0$ where $\mathbf{W}^{(-i)}_t$ stacks $\mathbf{W}^{(j)}_t$ for all firms relevant for company i appearing in $\widehat{\mathbf{VaR}}^{(-i)}_{q,t}$. Hence, with both quantile regression steps being linear, inserting (3) into (11) yields a full model for the system's tail risk in observable characteristics. However, direct one-step estimation is only feasible if the choice of $\mathbf{W}^{(i)}$ and thus $\mathbf{VaR}^{(-i)}_{q,t}$ is still determined in a pre-step from individual VaR regressions. Model selection based on the full model of VaR^s in observables is infeasible since correlation effects among the huge number of regressors would produce unreliable results. Furthermore, individual parameters $\beta^{s|i}_{0,p,q}$ and $\boldsymbol{\eta}^{s|i}_{p,q}$ could not be identified without additional identification condition $Q_q(\varepsilon^i_t|\mathbf{W}^{(i)}_t) = 0$, implicitly bringing back the first-step estimation. Therefore we use two-step estimation even if exact asymptotic confidence intervals are larger than for an (infeasible) single step procedure. In contrast to mean regressions, such results are non-standard in a quantile setting and are therefore provided in detail in Appendix A.1. In finite samples, however, asymptotic distributions often only provide a poor approximation to the true distribution of the (scaled) difference between the estimator and the true value if sample sizes are not sufficiently large. In case of quantile regressions, this effect is even more pronounced, since valid estimates for the asymptotic variance have poor non-parametric rates and thus require even larger sample sizes to obtain the same precision.

Therefore, we suggest a procedure for testing significance and potential time-variation of $\hat{\beta}^{s|i}_{p,q,t}$ which is valid in finite samples. For a given hypothesis H_0, we use the test statistic

$$S_T = \min_{\boldsymbol{\xi}^s \in \Omega_0} \sum_{t=1}^{T} \rho_p(X^s_t - \mathbf{B}'_t\boldsymbol{\xi}^s) - \min_{\boldsymbol{\xi}^s \in \mathbb{R}^{K_B}} \sum_{t=1}^{T} \rho_p(X^s_t - \mathbf{B}'_t\boldsymbol{\xi}^s), \tag{15}$$

with the compound vector of all regressors in VaR^s, $\mathbf{B}_t \equiv (VaR^i_t, VaR^i_t \cdot \mathbf{Z}^i_{t-1}, \mathbf{V}^{(i)}_t)$, corresponding K_B-parameter vector $\boldsymbol{\xi}^s$, and Ω_0 referring to the constrained set of parameters under H_0. This test is an adaptation to the quantile setting of a method proposed by Chen, Ying, Zhang, and Zhao (2008) for median regressions. Direct operationalization of the test is complicated by the fact that the asymptotic distribution of 15 involves unknown terms, and, secondly, by the nonsmooth objective function of the quantile regression, which causes inconsistency of conventional resampling techniques. Therefore, following Chen, Ying, Zhang, and Zhao (2008) we apply an adjusted bootstrap method, which is described in detail in Appendix A.4.

3.3 Empirical Evidence on Systemic Risk Betas and Risk Rankings

We estimate systemic risk betas according to (12) with time variation in firm-specific characteristics (i.e. $\mathbf{Z}_t^i = C_t^i$). As in the first-step estimations, we choose $q = 0.05$, i.e., we model the loss which will not be exceeded with 95% probability. For notational convenience, we suppress the quantile index as we set $p = q$. Obtained realized systemic risk betas indeed contain information on systemic relevance beyond a company's network interconnectedness. This is illustrated in Figure 4 revealing only slightly positive dependencies between pagerank coefficients and realized systemic risk betas. Thus, more connected firms tend to be systemically more risky, see e.g. , Bank of America and American Express. With an R^2 of 2% in the regression, the relationship, however, is not very strong indicating that the quantification of a firm's interconnectedness is not sufficient to assess its systemic relevance which directly depends on firm-specific and macroeconomic conditions. The latter is captured by realized systemic risk contributions but not necessarily by pagerank coefficients.

We statistically assess if a company's risk has a relevant direct impact on the system by testing for the significance of the respective systemic risk beta. Evaluating whether $\beta_t^{s|i} = 0$ requires testing for the joint significance of all variables driving a firm's marginal impact. Thus, we test the hypothesis

$$\mathbf{H1} : \beta_0^{s|i} = \eta_{MMM}^{s|i} = \eta_{SIZE}^{s|i} = \eta_{LEV}^{s|i} = \eta_{BM}^{s|i} = \eta_{VOL}^{s|i} = 0.$$

Whether marginal effects on the system are indeed time-varying in firm-specific characteristics can be tested by the joint hypothesis

$$\mathbf{H2} : \eta_{MMM}^{s|i} = \eta_{SIZE}^{s|i} = \eta_{LEV}^{s|i} = \eta_{BM}^{s|i} = \eta_{VOL}^{s|i} = 0.$$

If this hypothesis is not rejected, we re-specify the systemic risk beta as being constant, i.e., $\beta_t^{s|i} = \beta^{s|i}$, re-estimate the model without interaction variables and test the hypothesis

$$\textbf{H3} : \beta^{s|i} = 0 \; .$$

We find the majority of firms having a significant systemic risk beta which is classified as being time-varying in approximately 50% of all cases. In contrast, for approximately 25% of all firms we do not find systemic risk betas which are significantly different from zero. Table 4 reports the p-values of the respective underlying tests which are performed using the wild bootstrap procedure illustrated in Appendix A.4 based on $2,000$ resamples of the test statistic.[15] We consider effects as being significant if p-values are below 10%. Then, a company is defined as systemically relevant if an increase in its possible loss position, given all economic state variables and i-specific risk inflows from other companies, induces a significantly higher potential systemic loss. This requires its systemic risk beta to be significant *and* nonnegative.[16]

Table 5 lists all systemically relevant companies for the period from 2000 to 2008, ranked according to their average realized systemic risk contributions $\bar{\hat{\beta}}^{s|i}$. JP Morgan, American Express, Bank of America and Citigroup are identified as the (on average) most systemically risky companies. According to our network analysis above, these firms are categorized into the group of risk amplifiers which are strongly interconnected and should be closely supervised. To judge the validity and quality of our assessment based on market data, we compare our results with the outcomes of the Supervisory Capital Assessment Program (SCAP) conducted by the Federal Reserve in spring 2009, right after the end of our sample period. In this analysis, the Fed could draw on detailed non-public confidential balance sheet information to classify the 19 largest bank holding companies according to

[15]Because of multi-collinearity of time variation effects in firm characteristics for systemic risk betas, the interpretation of individual coefficients η might be misleading. Therefore, we refrain from reporting respective estimates.

[16]Since we do not impose a priori non-negativity restrictions, systemic risk betas can become negative at certain points in time. In a few cases we can directly attribute these effects to sudden time variations in one of the (interpolated) company-specific characteristics $\mathbf{Z}_{t-1}^i$ driving systemic risk betas temporarily into the negative region. These effects might be reduced by linking $\beta^{s|i}$ in (10) to (local) time averages of $\mathbf{Z}_{t-1}^i$. Such a proceeding would stabilize systemic risk betas but at the cost of a potentially high loss of information.

estimates of potential lack in capital buffer for covering risks under an adverse macro scenario. For details, see Federal Reserve System (2009). The financial institution with the biggest potential lack of capital buffer according to the SCAP, Bank of America, ranks among our highest systemically relevant companies leading the ranking in June 2008 (Table 6 b). In addition, with Citigroup, FifthThird Bancorp, Morgan Stanley, PNC, Regions Financial and Wells Fargo we identify six out of eight banks contained in our database[17] which, according to the SCAP results, were threatened by financial distress under more adverse market conditions. As we could in advance detect systemic riskiness of the majority of companies that were later found to face capital shortages in the stress test scenario of the SCAP, this confirms the quality of our method which is entirely based on only publicly available data.

Average systemic risk betas, however, only provide a rough picture of systemic importance as they aggregate companies' marginal systemic risk contributions and VaRs over time ignoring potential changes in the structure of the financial sector. In contrast, monitoring the evolution of systemic risk beta's over time provides a more informative picture on companies' specific systemic importance and yields valuable feedback from the market for forward-looking regulation. To illustrate the potential of our approach, we show the rankings at two specific time points: Table 6a gives the systemic risk ranking for the last week in March 2007, which was a relatively "calm" time before the start of the financial crisis. Table 6b, on the other hand, shows the ranking at the end of June 2008, shortly before the collapse of Lehman Brothers. Comparing the pre-crisis and post-crisis rankings, we observe clear changes. In most cases, systemic risk betas – and thus the magnitude of systemic risk contributions – significantly increased during the crisis. This is particularly observed for American Express, Bank of America, JP Morgan, Regions Financial and State Street, among others. Nevertheless, in some cases, as, e.g., for Citigroup and Morgan Stanley systemic risk contributions even declined.

During the crisis, we detect Bank of America as systemically most relevant. Our estimates indicate that its multiple risk channels in the center of the network, particularly to Morgan Stanley, American Express, Citigroup, Wells Fargo are systemically critical. Fig-

[17] Due to a lack of data, we cannot include KeyCorp and GMAC in our analysis which also have been found to be financially distressed in a critical macroeconomic environment.

ure 8 shows that Bank of America's systemic risk beta has been relatively stable before the financial crisis but significantly dropped after the issuance of the Federal Reserve's rescue packages. Nevertheless, its VaR and thus its realized systemic risk contribution strongly increased during the crisis. Our results also identify AIG as highly systemically relevant. Before the crisis, AIG was among the largest issuers and holders of credit default swaps (CDS) and other credit securitization derivatives. Its obviously strong exposure to mortgage default risks is reflected by a strong dependence to Freddie Mac and Fannie Mae, among others, as depicted in the network graph in Figure 5. The high systemic relevance of AIG is illustrated in the upper part of Figure 8 depicting $\beta_t^{s|i}$, VaR_t^i and the product thereof, $\bar{\beta}_t^{s|i}$. In 2008, AIG faced tremendous write-downs which caused strong increases of the firm's VaR and the realized systemic risk contribution $\bar{\beta}_t^{s|i}$. The rescue packages from the Federal Reserve amounting to USD 150 billion (see Schich, 2009) in September 2008, however, significantly reduced the risk of both AIG's and the entire system's failure. This is indicated by the strong decline of the companies' systemic risk beta in Figure 8). Due to the forward-looking character of systemic risk betas, the (anticipated) bailout has already been incorporated in the systemic risk ranking of end of June 2009 where AIG drops out of the list of systemically relevant companies. This is induced by strong changes in the companies' book-to-market ratio driving the systemic risk beta of AIG into the negative region.

By construction, realized systemic risk contributions $\bar{\beta}_t^{s|i}$ might vary over time through two channels: a time-varying beta, $\beta_t^{s|i}$ and a time-varying Value-at-Risk, VaR_t^i. For selected companies, these effects are illustrated by Figure 2 in the introduction. In many cases we observe increases of realized systemic risk contributions which are mainly due to rising individual VaRs with systemic risk betas which even slightly decline from 2007 to 2008. Hence, companies' *marginal* contribution to the system VaR is widely unchanged while their exposure to idiosyncratic risk resulting from worse firm-specific and macroeconomic conditions has been dramatically increased. See, for instance, the first two companies in the 2008 ranking, Bank of America and American Express which, however, realize quite different combinations of marginal systemic contributions and idiosyncratic tail risk levels apparently facing different sources for systemic relevance. In both cases, the strong increase in VaR can be attributed to tail risk spillovers in the network, with,

e.g., Bank of America being particularly affected by Citigroup and Morgan Stanley.
In several cases, increasing individual VaRs coincide with rising systemic risk betas. For instance, Wells Fargo is an example of a company which was not even identified as being systemically relevant in 2007 but faces a dramatic increase of both its systemic risk beta and its idiosyncratic tail risk making it highly systemically risky in 2008. Likewise, State Street, Progressive Ohio and Marshall & Isle (MI) face an increase of both $\beta_t^{s|i}$ and VaR_t^i. Also here, sources for increasing effects can be found in the network structure. An exception is State Street which does not face significant risk spillovers from other companies and thus primarily depends on micro- and macroeconomic externalities. As a result, the company's high systemic relevance in 2008 is due to the combination of a moderately high systemic risk beta and severe idiosyncratic risk which in turn affect balance sheets and obligations of other firms. For two central nodes in the network, Citigroup and Morgan Stanley, however, declining systemic risk betas overcompensate increasing VaRs resulting in declining systemic relevance.

The results illustrate that realized systemic risk contributions conveniently condense information on banks' systemic importance. Though, the underlying driving forces of a bank's changed systemic relevance can be quite different. Therefore, only simultaneously analyzing and monitoring (i) network effects, (ii) sensitivity to micro- and macroeconomic conditions and (iii) time-variations in systemic risk betas provide the full picture of companies' specific role in the network and thus build a solid basis for regulatory measures.

4 Validity: Pre-Crisis Period

In the course of the financial crisis 2007-2009, a number of large institutions defaulted, were overtaken by others or supported by the government. As for our general empirical study, we required data for all considered institutions to be available over the entire period from beginning of 2000 to end of 2008, some of these companies could not be included. Nevertheless, to validate and robustify our findings, we perform an additional analysis by re-estimating the model for the time period of January 1, 2000, to June 30, 2007 and including the investment banks Lehman Brothers and Merrill Lynch.

Because of the shorter estimation period, differences between estimated systemic risk contributions are not as pronounced as in the analysis covering the full time period. Therefore, as a sharp ranking of companies might not be very meaningful and hard to interpret in this context, Table 7 rather categorizes firms into groups according to quartiles of the distribution of realized systemic risk betas. Accordingly, we can distinguish between four broad classes: Firstly, there are 9 companies with VaRs that significantly influence the system VaR and are among the 25% largest average realized betas. The most prominent members of this group are AIG, Lehman Brothers, Morgan Stanley, JP Morgan and Goldman Sachs. The second group comprises systemically risky companies with significant systemic impact, whose average realized betas lie in the third quartile of the distribution. According to the estimates reported in Table 7, these magnitudes reflect a comparably high systemic relevance.[18] Group 2 group contains mainly large depositories and investment banks including Bank of America, Merrill Lynch, Citigroup and Regions Financial, but also the mortage company Freddie Mac. Group 3 includes all companies with small but significant average systemic risk betas, in particular those below the median. Finally, the ones which, according to the significance test, are not considered as being systemically risky during the analyzed time period, are collected in Group 4.

In detail, we focus on four companies which were massively affected by the crisis: *Lehman Brothers* became insolvent on September 15, 2008, and was liquidated afterwards. *Merrill Lynch* announced a merger with Bank of America in September 2008, which was executed on January 1, 2009. Furthermore, excluding the crisis period itself may reveal the systemic relevance of the mortgage firm *Freddie Mac*, which is closely connected to the second largest real estate financing company *Fannie Mae*. Both were placed under conservatorship by the U.S. government during the course of the financial crisis. Finally, it is interesting to investigate the systemic riskiness of *AIG*, which faced major distress during the crisis and whose bailout was very expensive for the tax payers. As shown by Table 7 (with the specific companies marked in bold), all of these firms be-

[18]For a better exposition, we multiply all values of realized systemic risk betas with 100.

long to the group of systemically relevant firms with high or mid-sized average systemic risk betas.

Table 8 summarizes the results of our empirical analysis for the four case study candidates using only the pre-crisis data. Our network analysis reveals that almost all of the companies are subject to loss spillovers from direct competitors: Freddie Mac is influenced by risk transmissions of Fannie Mae, and vice versa. Despite Fannie Mae's low average realized systemic risk beta, this direct bi-directional risk dependence reveals the company's systemic relevance. Merrill Lynch influences Citigroup (C). TD Ameritrade Holding (AMTD) and E Trade Financial (ETFC) are large online brokers which operate on the same market as Lehman and Merrill Lynch and are identified as significant tail risk producer and receiver, respectively. Likewise, we identify tail risk dependencies between Lehman and both Morgan Stanley and Goldman Sachs, being Lehman's main competitors and the two largest investment banks in the U.S. during the estimation period. AIG is clearly the most interconnected firm in this case study. Its VaR is affected by the tail risks of eight competing insurers: Allstate (ALL), Chubb (CB), Hartford Financial (HIG), Lincoln National Corp. (LNC), MBIA, Marsh & McLennan Inc. (MMC), and Torchmark (TMK) as well as by Lehman Brothers (LEH). There are mutual spillovers with Citigroup, ETFC, CNA, HIG, and MMC. Additionally, AIG's losses have an effect on the VaRs of another three insurance companies, Aflac (AFL), Humana (HUM) and Unum (UNM).

All four companies of interest have a significant impact on the system. Focussing particularly on Lehman Brothers and Merrill Lynch, we show the time evolution of their realized risk betas and VaRs in Figures 9 and 10, respectively. It turns out that the realized systemic risk beta of Lehman steadily increases from 2005 to 2007. Interestingly, its VaR only increases in the second half of 2005 but remains widely on the same level afterwards. Hence, its growing systemic relevance is mainly due to rising marginal effects on the system and is not reflected in Lehman's idiosyncratic risk exposure. The jumps in the VaR (and thus also in the realized risk beta) are induced by relevant loss exceedances which only occur whenever one of Lehman's tail risk drivers (e.g., Morgan Stanley) exceeds his (unconditional 10%) loss quantile. This discreteness reflects the company's tail risk sensitivity to loss exceedances of competitors.

In case of Merrill Lynch, we observe high fluctuations of the realized systemic risk beta over the analyzed time period. As for Lehman Brothers, we observe clear differences in the paths of our systemic risk measure and VaR. For example, while its VaR, apart from some fluctuations keeps returning to the same level, its realized risk beta increases by more than 100% from mid of 2006 to mid of 2007. Hence, also here, the (realized) systemic risk beta reveals information on the company's systemic importance which cannot be detected by an analysis of the VaR solely. This finding strongly backs the usefulness of our proposed measure.

From these results, which are produced only from pre-crisis data, we can infer that in June 2007, each of the five financial institutions of interest was classified as being relevant for the stability of the U.S. financial system. Our findings indicate, firstly, that bailouts during the crisis were justified for Fannie Mae, Freddie Mac and AIG. Also a failure of Merrill Lynch would have led to harsh systemic consequences which could be prevented by its merger with Bank of America in 2008. Secondly, the increasing systemic importance of Lehman Brothers could have been monitored and thus the impact of its bankruptcy could have been anticipated to a certain extent. The direct bi-directional linkage to JP Morgan, as well as the connections to Morgan Stanley and Goldman Sachs, which in turn are deeply interconnected, indicate a high risk for contagion as a result of Lehman's failure. Furthermore, our estimates show that Lehman's systemic risk contribution is only slightly lower than that of AIG, while it is substantially higher than that of, e.g., Freddie Mac. Given these results, bailing out the latter but not the former is not necessarily justifiable from a systemic risk management point of view. If these results had existed in advance, more effective regulatory measures could have been performed which could have helped reducing the extent of the financial crisis.

5 Conclusion

The worldwide financial crisis 2007-2009 has revealed that there is a need for a better understanding of systemic risk. Particularly in situations of distress, it is the interconnectedness of financial companies which plays a major role but challenges quantitative analysis and the construction of appropriate risk measures.

In this paper, we propose a measure of firms' systemic relevance which accounts for dependence structures within the financial network given market externalities. Our analysis allows to statistically identify relevant channels of potential tail risk spillovers between firms constituting the topology of the financial network. Based on these relevant company-specific risk drivers, we measure a firm's idiosyncratic tail risk by explicitly accounting for its interconnectedness with other institutions. Our measure for a company's systemic risk contribution quantifies the impact on the risk of distress of the system induced by an increase in the risk of the specific company in a network setting. Both measures exclusively rely on publicly observable balance sheet and market characteristics and can thus be used for predictions in a stress test scenario.

Our empirical results show the interconnectedness of the U.S. financial system and clearly mark channels of relevant potential risk spillovers. In particular, we can classify companies into major risk producers, transmitters or recipients within the system. Moreover, at any specific point in time, firms can be ranked according to their estimated contribution to systemic risk given their role and position in the network. Monitoring companies' systemic relevance over time, thus allows to detect those firms which are most central for the stability of the system. In a case study, we highlight that our approach could have served as a solid basis for sensible forward-looking regulation before the start of the financial crisis in 2007.

Our approach is readily extendable in several directions. In particular, although the financial system is dominated by the U.S, it truly is a global business with many firms operating internationally. Detecting inter- and intra-country risk connections and measuring firms' global systemic relevance, should be straightforward with our proposed methodology. Moreover, whenever additional (firm-specific or market-wide) information is available as, e.g., reported to central banks, it can be directly incorporated into our measurement procedure. The data-driven selection step of relevant risk drivers then determines if and how it increases the precision of results.

Appendix A Econometric Methodology

A.1 Asymptotic Results for Two-Step Quantile Estimation

Under the adaptive choice of penalty parameter as described in the text, the LASSO selection method is consistent with rate $O_P(\sqrt{\frac{K(i)}{T}\log(\max(K,T)})$, and with high probability the coefficients selected of **W**, contain the the true coefficients also in finite samples. These results follow directly from Belloni and Chernozhukov (2011). Furthermore, VaR^i is consistently estimated by the post-LASSO method described in the text which re-estimates the unrestricted model with $\mathbf{W}^{(i)}$. In particular, for all $q \in I$ with $I \in (0,1)$ being compact,

$$\hat{\boldsymbol{\xi}}_q^i - \boldsymbol{\xi}_q^i \leq O_P(\sqrt{\frac{K(i)}{T}\log(\max(K,T))}), \tag{A1}$$

since in our setting it is safe to assume that the number of wrongly selected components of **W** is stochastically bounded by the number $K(i)$ of components of **W** contained in the true model for VaR^i (see equation (2.16) in Belloni and Chernozhukov (2011)). We write in a slight abuse of notation $Y_T \leq O_P(r_T)$, with Y_T being either $O_P(r_T)$ or even $o_P(r_T)$ for any random sequence Y_T and deterministic $r_T \to 0$. Note that in general for $T \to \infty$, both K and $K(i)$ might grow only extremely slowly in T, such that they can be treated close to being constants implying the standard oracle bound $O_P(\sqrt{\frac{\log(T)}{T}})$ in (A1).

If the true model is selected, we find for the asymptotic distribution of the individual VaR estimates for any $q \in [0,1]$,[19]

$$\sqrt{\frac{1}{T}}\left(\hat{\boldsymbol{\xi}}_q^i - \boldsymbol{\xi}_q^i\right)' \to N\left(0, \frac{q(1-q)}{g^2(G^{-1}(q))}\mathbb{E}[\mathbf{W}^{(i)}\mathbf{W}^{(i)\prime}]^{-1}\right) \ , \tag{A2}$$

where $g(G^{-1}(q))$ denotes the density of the corresponding error ε^i distribution at the qth quantile. This result is standard (see Koenker and Bassett, 1978). For the second step estimates, we derive the asymptotic distribution analogously to the two-step median results in Powell (1983)

$$\sqrt{\frac{K(i)}{T}}\left((\hat{\beta}_{0,p,q}^{s|i}, \hat{\boldsymbol{\eta}}_{p,q}^{s|i}, \hat{\boldsymbol{\gamma}}_p^s)' - (\beta_{0,p,q}^{s|i}, \boldsymbol{\eta}_{p,q}^{s|i}, \boldsymbol{\gamma}_{\boldsymbol{p}}^{\boldsymbol{s}})'\right) \tag{A3}$$

$$\to \mathcal{N}\left(0, Q^{-1}\mathbb{E}\left[\frac{p(1-p)}{f^2(F^{-1}(p))}\rho_p(\varepsilon_t^s) - \frac{p(1-p)}{g^2(G^{-1}(p))}\beta_{p,q}^{s|i\prime}\left(\rho_p(\varepsilon_t^i), \rho_p^v(\mathbf{Z}_{t-1}\varepsilon_t^i)\right)\right]\right) \ , \tag{A4}$$

[19]Required assumptions of Belloni and Chernozhukov (2011) and quantile analogies to Powell (1983) are fulfilled in our setting.

where in the scalar factor, $f(F^{-1}(p))$ is the density of the corresponding error ε^s at the pth quantile, the function ρ_p^v of a vector applies ρ_p to each of its components, and $\beta_{p,q}^{s|i} = (\beta_{0,p,q}^{s|i}, \boldsymbol{\eta}_{p,q}^{s|i})$. The remaining main part Q in the variance is given by $Q = H'\mathbb{E}[\mathbf{A}\mathbf{A}']H$ with $\mathbf{A} = (\mathbf{W}^{(i)}, vec(\mathbf{Z}_{t-1} \cdot \mathbf{W}^{(i)\prime}), \mathbf{VaR}^{(-i)})$. Denote by $\mathbf{I}$ and $\mathbf{0}$ identity and null matrices, respectively, and by $\mathbf{1}$ a vector of ones of appropriate dimension. Then,

$$H' = \begin{pmatrix} \mathrm{diag}(\boldsymbol{\xi}_{q,2}^i) & \mathbf{0} & \cdots\mathbf{0}\cdots & \cdots\mathbf{0}\cdots \\ \mathbf{0} & \mathrm{diag}(\boldsymbol{\xi}_{q,1}^i) & \cdots\mathbf{0}\cdots & \cdots\mathbf{0}\cdots \\ \mathbf{0} & \mathbf{0} & \mathrm{diag}(vec(\mathbf{1}_{d_z} \cdot \boldsymbol{\xi}_q^{i\prime})) & \cdots\mathbf{0}\cdots \\ \mathbf{I} & \mathbf{0} & \cdots\mathbf{0}\cdots & \cdots\mathbf{0}\cdots \\ \mathbf{0} & \mathbf{0} & \cdots\mathbf{0}\cdots & \mathbf{I}_{d_{(-i)} \times d_{(-i)}} \end{pmatrix}$$

where d_Z is the dimension of Z which is 3 in our application, $d_{(-i)}$ is the dimension of $\mathbf{VaR}_t^{(-i)}$, and coefficients $\boldsymbol{\xi}_{q,2}^i$ are those components of $\boldsymbol{\xi}_q^i$ for regressors which appear both in the first and the second step. Correspondingly, $\boldsymbol{\xi}_{q,1}^i$ are coefficients of regressors which just appear in the first step of the individual VaR regression. Note that in the variance matrix there is a distinction in $\boldsymbol{\gamma}$ for parts of $\mathbf{V}$ which are also controls in VaR^i and $\mathbf{VaR}_t^{(-i)}$, which just appear in VaR^s.

A.2 Choice of the Company-specific LASSO penalty parameter λ^i

We determine λ^i in a data-driven way following a bootstrap type procedure as suggested by Belloni and Chernozhukov (2011):

Step 1 Take T iid draws from $\mathcal{U}[0,1]$ independent of $\mathbf{W}_1, \ldots, \mathbf{W}_T$ denoted as $U_1, \ldots, U_T$. Conditional on observations of $\mathbf{W}$, calculate the corresponding value of the random variable,

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

Step 2 Repeat step 1 for B=500 times generating the empirical distribution of Λ^i conditional on $\mathbf{W}$ through $\Lambda_1^i, \ldots, \Lambda_B^i$. For a confidence level $\alpha \leq 1/K$ in the selection, set

$$\lambda^i = c \cdot Q(\Lambda^i, 1 - \alpha | \mathbf{W}_t),$$

where $Q(\Lambda^i, 1-\alpha|\mathbf{W}_t)$ denotes the $(1-\alpha)$-quantile of Λ^i given $\mathbf{W}_t$ and $c \leq 2$ is a constant.

The choice of α is a trade-off between a high confidence level and a corresponding high regularization bias from high penalty levels in (7). As in the simulation results in Belloni and Chernozhukov (2011), we choose $\alpha = 0.1$, which suffices to get optimal rates of the post-penalization estimators below. Finally, the parameter c is selected in a data-dependent way such that the in-sample predictive ability of the resulting VaR specification is maximized. (Belloni and Chernozhukov (2011) proceed in a similar way). The latter is evaluated in terms of its best backtesting performance according to the procedure described below.

A.3 Backtest for the Model Fit for VaR^i

As suggested by Berkowitz, Christoffersen, and Pelletier (2009), for each institution i, we measure VaR exceedances as $I_t^i \equiv I(X_t^i < -VaR_{q,t}^i)$. If the chosen model is correct, then,

$$\mathbb{E}[I_t^i|\Omega_t] = q \; , \tag{A5}$$

where Ω_t is the information set up to t. The VaR is estimated correctly, if independently for each day of the covered period, the probability of exceeding the VaR equals q. Similar to Engle and Manganelli (2004), Kuester, Mittnik, and Paolella (2006) and Taylor (2008), we include a constant, three lagged values of I_t and the current VaR estimate in the information set Ω_t. Then, condition (A5) can be checked by estimating a logistic regression model

$$I_t^i = \alpha + \mathbf{A}_t' \boldsymbol{\theta} + U_t,$$

with covariates $\boldsymbol{A}_t = (I_{t-1}^i, I_{t-2}^i, I_{t-3}^i, \widehat{VaR}_{t-1}^i)'$. Denote by $\bar{I}^i$ the sample mean of the binary response I_t^i and define $F_{log}(\cdot)$ as the cumulative distribution function of the logistic distribution. Then, under the joint hypothesis

$$\mathbf{H}_0 : \; \alpha = q \text{ and } \boldsymbol{\theta}_1 = \cdots \boldsymbol{\theta}_4 = 0,$$

the asymptotic distribution of the corresponding likelihood ratio test statistic is

$$LR = -2(\ln \mathcal{L}_r - \ln \mathcal{L}_u) \overset{a}{\sim} \chi_5^2 \; . \tag{A6}$$

Here, $\ln \mathcal{L}_u = \sum_{t=1}^{n} \left[I_t^i \ln F_{log}(\alpha + \mathbf{A}_t'\boldsymbol{\theta}) + (1 - I_t^i) \ln \left(1 - F_{log}(\alpha + \mathbf{A}_t'\boldsymbol{\theta}) \right) \right]$ is the unrestricted log likelihood function which under $\mathbf{H}_0$ simplifies to $\ln \mathcal{L}_r = n\bar{I}^i \ln(q) + n(1 - \bar{I}^i) \ln(1 - q)$.

A.4 Bootstrap Procedure for the Joint Significance Test

The asymptotic distribution of the test statistic introduced in Section 3.2,

$$S_T = \min_{\boldsymbol{\xi}^s \in \Omega_0} \sum_{t=1}^{T} \rho_p(X_t^s - \mathbf{B}_t'\boldsymbol{\xi}^s) - \min_{\boldsymbol{\xi}^s \in \mathbb{R}^{K_B}} \sum_{t=1}^{T} \rho_p(X_t^s - \mathbf{B}_t'\boldsymbol{\xi}^s), \tag{A7}$$

involves the probability density function of the underlying error terms and is not feasible. Furthermore, bootstrapping S_T directly would yield inconsistent results. Therefore, we re-sample from the adjusted statistic

$$\begin{aligned} S_T^* \quad = \quad & \min_{\boldsymbol{\xi}^s \in \Omega_0} \sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t'\boldsymbol{\xi}^s) - \min_{\boldsymbol{\xi}^s \in \mathbb{R}^{K_B}} \sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t'\boldsymbol{\xi}^s) \\ & - \left(\sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t'\hat{\boldsymbol{\xi}}_c^s) - \sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t'\hat{\boldsymbol{\xi}}^s) \right), \end{aligned} \tag{A8}$$

where $\hat{\boldsymbol{\xi}}_c^s$ denotes the constrained estimate of $\boldsymbol{\xi}^s$, and $\{w_t\}$ is a sequence of standard exponentially distributed random variables, having both mean and variance equal to one. According to Chen, Ying, Zhang, and Zhao (2008), the empirical distribution of S_T^* provides a good approximation of the distribution of S_T. Thus, if the test statistic S_T exceeds some large quantile of the re-sampling distribution of S_T^*, the null hypothesis is rejected.

The proposed testing method does not require re-sampling of observations but is entirely based on the original sample. This provides significant gains in accuracy in the two-step regression setting as opposed to standard pairwise bootstrap techniques as a further alternative. A pre-analysis shows that this wild bootstrap type procedure is valid in the presented form as any serial dependence in the data is sufficiently captured by the regressors in the reduced-form relation not requiring block-bootstrap techniques.[20]

[20] Pairwise block-bootstrap yields block lengths of one according to the standard procedure of Lahiri (2001). Results are available upon request.

Appendix B Tables and Figures

Table 1: Included financial institutions in alphabetical order within sectors.

Depositories (21)	**Others (11)**	**Insurance Comp. (20)**
BB T Corp (BBT)	American Express Co (AXP)	AFLAC Inc (AFL)
Bank of New York Mellon (BK)	Eaton Vance Corp (EV)	Allstate Corp (ALL)
Bank of America Corp (BAC)	Fed. Home Loan Mortg. Corp (FRE)	American International Group (AIG)
Citigroup Inc (C)	Fed. National Mortgage Assn (FNM)	AON Corp (AON)
Comerica Inc (CMA)	Fifth Third Bancorp (FITB)	Berkley WR Corp (WRB)
Hudson City Bancorp Inc. (HCBK)	Franklin Resources Inc (BEN)	CIGNA Corp (CI)
Huntington Bancshares Inc. (HBAN)	Legg Mason Inc (LM)	C N A Financial Corp. (CNA)
JP Morgan Chase & Co (JPM)	Leucadia National Corp (LUK)	Chubb Corp (CB)
M & T Bank Corp. (MTB)	SEI Investments Company (SEIC)	Cincinnati Financial Corp (CINF)
Marshall & Ilsley Corp (MI)	TD Ameritrade Holding Corp (AMTD)	Coventry Health Care Inc (CVH)
NY Community Bankcorp (NYB)	Union Pacific Corp (UNP)	Hartford Financial (HIG)
Northern Trust Corp (NTRS)		HEALTH NET INC (HNT)
Peoples United Financial Inc. (PBCT)	**Broker-Dealers (7)**	Humana Inc (HUM)
PNC Financial Services Group (PNC)	E Trade Financial Corp (ETFC)	Lincoln National Corp. (LNC)
Financial Corp New (RF)	Goldman Sachs Group Inc (GS)	Loews Corp (L)
S L M Corp.	Lehman Brothers (LEH)*	Marsh & McLennan Inc. (MMC)
State Street Corp (STT)	Merrill Lynch (ML)*	MBIA Inc (MBI)
Suntrust Banks Inc (STI)	Morgan Stanley Dean Witter & Co (MS)	Progressive Corp Ohio (PGR)
Synovus Financial Corp (SNV)	Schwab Charles Corp New (SCHW)	Torchmark Corp (TMK)
Wells Fargo & Co (WFC)	T Rowe Price Group Inc. (TROW)	Unum Group (UNM)
Zions Bancorp (ZION)		

* included only in the case study

Table 2: Exemplary post-LASSO quantile regressions for VaR^i with $q = 0.05$. Regressors were selected by LASSO as outlined in Secion 2.1. Ex.j is the loss exceedance of company j, all other regressors are as in Section 1.2.

	Value	Std. Error	t-ratio	p-value
		Goldman Sachs		
(Intercept)	-0.046	0.004	-12.54	0.000
Ex.C	-0.239	0.205	-1.17	0.243
Ex.JPM	-0.014	0.119	-0.121	0.904
Ex.LM	-0.215	0.111	-1.932	0.054
Ex.MS	-0.403	0.079	-5.096	0.000
Ex.SCHW	-0.282	0.244	-1.153	0.249
		Morgan Stanley		
(Intercept)	-0.041	0.003	-16.017	0.000
Ex.AIG	-0.106	0.026	-4.036	0.000
Ex.AON	0.445	0.145	3.066	0.002
Ex.BAC	-0.604	0.145	-4.157	0.000
Ex.EV	-0.158	0.134	-1.179	0.239
Ex.GS	-0.634	0.121	-5.236	0.000
Ex.HBAN	-0.273	0.136	-2.006	0.045
Ex.HCBK	-0.452	0.28	-1.611	0.108
Ex.MTB	-0.269	0.193	-1.392	0.165
Ex.SCHW	-0.381	0.116	-3.294	0.001
Ex.SEIC	-0.229	0.154	-1.485	0.138
Ex.STT	-0.174	0.176	-0.986	0.325
		Regions Financial		
(Intercept)	-0.004	0.004	-1.072	0.284
Ex.AMTD	-0.091	0.04	-2.274	0.023
Ex.AON	-0.256	0.086	-2.998	0.003
Ex.BBT	-0.307	0.104	-2.95	0.003
Ex.FITB	0.032	0.087	0.37	0.712
Ex.HBAN	-0.042	0.064	-0.661	0.509
Ex.PBCT	-0.307	0.085	-3.598	0
Ex.STI	-0.244	0.114	-2.137	0.033
Ex.ZION	-0.196	0.1	-1.947	0.052
BM	0.024	0.007	3.221	0.001
VOL	0.251	0.16	1.568	0.118
		Fannie Mae		
(Intercept)	-0.049	0.003	-17.075	0.000
Ex.AIG	-0.227	0.231	-0.981	0.327
Ex.FRE	-1.007	0.121	-8.298	0.000

	Value	Std. Error	t-ratio	p-value
		American International Group		
(Intercept)	-0.043	0.003	-14.026	0.000
Ex.FRE	-0.201	0.014	-14.033	0.000
Ex.MBI	-0.336	0.138	-2.423	0.016
Ex.RF	-0.455	0.051	-8.975	0.000
Ex.TMK	-0.813	0.721	-1.127	0.260
		Torchmark		
(Intercept)	-0.019	0.003	-7.203	0
Ex.AFL	-0.332	0.169	-1.962	0.05
Ex.ALL	-0.256	0.207	-1.237	0.217
Ex.BBT	-0.296	0.223	-1.329	0.184
Ex.HIG	-0.084	0.175	-0.483	0.63
Ex.LNC	0.002	0.135	0.018	0.986
Ex.NTRS	-0.002	0.115	-0.015	0.988
Ex.SEIC	-0.243	0.12	-2.023	0.044
Ex.UNM	-0.088	0.179	-0.489	0.625
Ex.UNP	-0.242	0.242	-1	0.318
repo	0.031	0.017	1.78	0.076
		JP Morgan		
(Intercept)	-0.040	0.003	-12.963	0.000
Ex.BAC	-0.229	0.133	-1.724	0.085
Ex.BK	-0.237	0.129	-1.842	0.066
Ex.C	-0.380	0.22	-1.729	0.084
Ex.GS	-0.253	0.154	-1.648	0.199
Ex.PNC	-0.274	0.077	-3.583	0.000
Ex.SCHW	-0.410	0.118	-3.472	0.001
		American Express		
(Intercept)	-0.035	0.003	-11.723	0
Ex.AFL	-0.42	0.408	-1.03	0.303
Ex.BAC	-0.361	0.205	-1.757	0.08
Ex.BBT	-0.145	0.126	-1.151	0.25
Ex.BEN	-0.112	0.139	-0.808	0.42
Ex.CINF	-0.153	0.153	-0.999	0.318
Ex.EV	-0.181	0.163	-1.112	0.267
Ex.L	0.014	0.114	0.122	0.903
Ex.SEIC	-0.106	0.09	-1.186	0.236
Ex.SLM	0.073	0.067	1.09	0.276
Ex.STT	-0.351	0.159	-2.2	0.028
Ex.TROW	-0.3	0.126	-2.39	0.017

Table 3: Tail risk cross dependencies: For each company, we list loss exceedances selected by LASSO as regressors for the VaR^i-model (q=0.05) ('Influencing companies') and companies for which the respective loss exceedance has been selected ('Influenced companies').

Name	Influencing companies	Influenced companies
	Broker Dealers	
ETFC	AMTD,GS,MS	AMTD,C
GS	C,JPM,LM,MS,SCHW	BEN,C,ETFC,JPM,LM,MS,SCHW
MS	AIG,AON,BAC,EV,GS,HBAN,HCBK,MTB,SCHW,SEIC,STT	AMTD,BAC,EV,GS,HUM,LNC,ETFC,SEIC
SCHW	AMTD,GS,JPM,NTRS,TROW	AMTD,MS,GS,JPM
TROW	AMTD,BEN,EV,JPM,LUK,NTRS,SEIC,SNV	AON,MBI,MMC,AMTD,AXP,BEN,EV,NTRS,SCHW
	Depositories	
BAC	AON,AXP,C,HBAN,LM,MS,MTB,PBCT,PNC,SEIC,STI,WFC	AXP,BBT,C,CMA,HCBK,JPM,LM,MBI,MS,MTB,PNC,STI,WFC
BBT	BAC,FITB,MTB,NTRS,STI,TMK,UNP,WFC	AXP,BEN,CMA,FRE,MTB,RF,TMK,UNP,WFC,ZION
BK	AXP,JPM,MTB,NTRS,SNV,STT,WFC	CMA,JPM,NTRS,SEIC,SNV
C	BAC,ETFC,FITB,GS,JPM,LNC,LUK,MBI,MTB	BAC,GS,JPM,LUK
CMA	AON,BAC,BBT,BK,HBAN,RF,SNV,WFC	AON,PNC,SNV,ZION
HBAN	AON,LNC,RF,STI,ZION	AON,BAC,CMA,EV,LNC,MS,PBCT,RF,ZION
HCBK	AON,BAC,MBI,MTB,NYB	MS,MTB
JPM	BAC,BK,C,GS,PNC,SCHW	BK,C,GS,SCHW,SEIC,TROW
MI	MMC,TMK	HIG,MMC
MTB	BAC,BBT,HCBK,NYB,SNV,ZION	AON,BAC,BBT,BK,HCBK,MS,SNV,WFC,ZION,C
NTRS	BEN,BK,LUK,MMC,SEIC,STT,TROW	AFL,AMTD,BBT,BEN,BK,HIG,MMC,PGR,SCHW,TMK,TROW,LUK,STT
NYB	PBCT,WFC	MTB,SLM,WFC,HCBK,PBCT
PBCT	HBAN,NYB	AON,BAC,CB,NYB,RF
PNC	BAC,CMA,STT,TMK,WFC,ZION	BAC,JPM,ZION
RF	AMTD,AON,BBT,FITB,HBAN,PBCT,STI,ZION	AIG,AON,CMA,EV,FITB,HBAN,MBI,SNV,STI,ZION
SLM	AON,AXP,FRE,MBI,NYB	AON,AXP,BEN,EV,FITB,MBI
SNV	BK,CMA,FITB,MTB,RF,ZION	BEN,BK,CMA,FITB,MTB,TROW
STI	AON,BAC,FITB,LNC,RF,WFC,ZION	AFL,AON,BAC,BBT,FITB,HBAN,RF,ZION,CINF,HUM,UNM,WFC
STT	AXP,NTRS	AXP,BK,NTRS,PNC,MS
WFC	BAC,BBT,CB,LNC,MTB,NYB,STI	FITB,PNC,STI,AFL,BAC,BBT,BK,CMA,NYB
ZION	BBT,CMA,HBAN,MTB,PNC,RF,STI	AON,RF,FITB,HBAN,LNC,MTB,PNC,SNV,STI
	Insurance Companies	
AFL	ALL,AON,CNA,EV,NTRS,SEIC,STI,TMK,WFC	AXP,CB,EV,PGR,TMK,UNM
AIG	FRE,MBI,RF,TMK	FNM,MBI,MS
ALL	CB,CNA,L,LNC,TMK	AFL,PGR,TMK,UNM
AON	CMA,HBAN,MBI,MTB,PBCT,RF,SLM,STI,TROW,ZION	AFL,BAC,BEN,CMA,EV,FITB,HBAN,HCBK,LM,MBI,MS,RF,SLM,STI
CB	AFL,L,LNC,PBCT,PGR	ALL,CINF,EV,HIG,L,WFC,WRB
CI	CNA,HNT,HUM,LNC	HNT,HUM,LNC
CINF	CB,MBI,STI	AXP,LM
CNA	EV,L,LNC,MBI	AFL,ALL,CI,L,LNC,MBI
CVH	HUM	SEIC
HIG	CB,L,LNC,MI,NTRS,TMK	HUM,LNC,TMK
HNT	CI,EV,HUM,LM,LNC,PGR	CI,HUM,LM
HUM	CI,HIG,HNT,MS,STI	CI,HNT
L	CB,CNA,LNC,TMK,UNP	ALL,AXP,CB,CNA,HIG,LNC,UNM,UNP
LNC	CI,CNA,EV,HBAN,HIG,L,MS,SEIC,TMK,ZION	ALL,C,CB,CNA,HBAN,HIG,HNT,L,SEIC,STI,TMK,UNM,WFC,CI
MBI	AIG,AON,BAC,BEN,CNA,FRE,RF,SLM,TROW	AIG,AON,BEN,C,CINF,HCBK,SLM,CNA,LM
MMC	MI,NTRS,PGR,SEIC,TROW,UNM	MI,NTRS,UNM
PGR	AFL,ALL,NTRS,WRB	MMC,CB,HNT,WRB
TMK	AFL,ALL,BBT,HIG,LNC,NTRS,SEIC,UNM,UNP	AFL,BBT,EV,L,LNC,MI,PNC,AIG,ALL,HIG
UNM	AFL,ALL,L,LNC,MMC,STI	TMK,MMC
WRB	BEN,CB,PGR	PGR
	Others	
AMTD	ETFC,MS,NTRS,SCHW,SEIC,TROW	ETFC,RF,SCHW,TROW
AXP	AFL,BAC,BBT,BEN,CINF,EV,L,SEIC,SLM,STT,TROW	BAC,BEN,BK,EV,SLM,STT
BEN	AON,AXP,BBT,EV,GS,LM,MBI,NTRS,SLM,SNV,TROW	AXP,EV,LM,MBI,NTRS,TROW,WRB
EV	AFL,AON,AXP,BEN,CB,HBAN,MS,RF,SEIC,SLM,TMK,TROW	AFL,AXP,BEN,CNA,FRE,HNT,LM,LNC,MS,TROW
FITB	AON,LUK,RF,SLM,SNV,STI,WFC,ZION	BBT,C,FRE,RF,SNV,STI
FNM	AIG,FRE	FRE
FRE	BBT,EV,FITB,FNM,LUK	AIG,MBI,SLM,FNM
LM	AON,BAC,BEN,CINF,EV,GS,HNT,MBI	BAC,BEN,GS,HNT,LUK
LUK	C,LM,NTRS	C,FITB,FRE,NTRS,TROW
SEIC	BK,CVH,JPM,LNC,MS	AFL,AMTD,AXP,BAC,EV,LNC,MMC,MS,NTRS,TMK,TROW
UNP	BBT,L	BBT,TMK,L

Table 4: p-values for the test on significance of systemic risk betas (Hypothesis H1) and for the test on constancy of systemic risk betas (Hypothesis H2). For the second panel, we include in parentheses the p-values for the test on significance of systemic risk betas in case $H1$ is rejected but $H2$ is not (Hypothesis H3).

Name	pv_{H1}	pv_{H2} (pv_{H3})
Companies with significant and time-varying $\beta_t^{s\|i}$		
AMERICAN EXPRESS	0.001	0.006
AMERICAN INTL.GP.	0.002	0.000
BANK OF AMERICA	0.002	0.001
CHARLES SCHWAB	0.019	0.013
CHUBB	0.017	0.015
CIGNA	0.001	0.013
CINCINNATI FINL.	0.010	0.004
CITIGROUP	0.026	0.066
COMERICA	0.016	0.020
FANNIE MAE	0.001	0.000
FIFTH THIRD BANCORP	0.039	0.021
FRANKLIN RESOURCES	0.028	0.030
FREDDIE MAC	0.098	0.092
HARTFORD FINL.SVS.GP.	0.001	0.001
HUDSON CITY BANC.	0.043	0.035
HUNTINGTON BCSH.	0.010	0.011
LEGG MASON	0.026	0.060
LEUCADIA NATIONAL	0.041	0.016
LINCOLN NAT.	0.062	0.026
M & T BK.	0.033	0.021
MARSH & MCLENNAN	0.003	0.002
MARSHALL & ILSLEY	0.020	0.019
MORGAN STANLEY	0.041	0.095
PNC FINANCIAL SVS. GP	0.012	0.012
PROGRESSIVE OHIO	0.007	0.003
REGIONS FINANCIAL	0.034	0.029
STATE STREET	0.054	0.049
T ROWE PRICE GP.	0.090	0.076
TORCHMARK	0.002	0.001
UNION PACIFIC	0.040	0.035
UNUM GROUP	0.079	0.097
W R BERKLEY	0.007	0.037
WELLS FARGO & CO	0.015	0.027
ZIONS BANCORP.	0.095	0.100
Companies with significant but constant $\beta^{s\|i}$		
AON	0.063	0.192 (0.135)
E TRADE FINANCIAL	0.072	0.160 (0.233)
JP MORGAN CHASE & CO.	0.014	0.237 (0.047)
NY.CMTY.BANC.	0.040	0.132 (0.088)
SEI INVESTMENTS	0.014	0.115 (0.025)
TD AMERITRADE HOLDING	0.049	0.131 (0.188)
Companies with insignificant $\beta^{s\|i}$		
AFLAC	0.220	-
ALLSTATE	0.114	-
BANK OF NEW YORK MELLON	0.199	-
BB &T	0.120	-
CNA FINANCIAL	0.410	-
COVENTRY HEALTH CARE	0.257	-
EATON VANCE NV.	0.276	-
GOLDMAN SACHS GP.	0.667	-
HEALTH NET	0.371	-
HUMANA	0.189	-
LOEWS	0.276	-
MBIA	0.235	-
NORTHERN TRUST	0.305	-
PEOPLES UNITED FINANCIAL	0.105	-
SLM	0.391	-
SUNTRUST BANKS	0.213	-
SYNOVUS FINL.	0.289	-

Table 5: Ranking of **average** systemic risk contributions based on realized systemic risk betas. The third column lists loss exceedances that are included in the respective company's VaR^i-regression. Estimation period 2000-2008 Q3. Systemic risk contributions based on time-varying betas are marked by *.

Rank	Name	$\widehat{\beta}^{s\|i}_{av} \cdot 10^2$	influencing companies
1	JP MORGAN CHASE & CO	1.41	BAC,BK,C,GS,PNC,SCHW
2	AMERICAN EXPRESS	1.22*	AFL,BAC,BBT,BEN,CINF,EV,L,SEIC,SLM,STT,TROW
3	BANK OF AMERICA	1.01*	AON,AXP,C,HBAN,LM,MS,MTB,PBCT,PNC,SEIC,STI,WFC
4	CITIGROUP	0.87*	BAC,ETFC,FITB,GS,JPM,LNC,LUK,MBI,MTB
5	LEGG MASON	0.83*	AON,BAC,BEN,CINF,EV,GS,HNT,MBI
6	REGIONS FINANCIAL	0.72*	AMTD,AON,BBT,FITB,HBAN,PBCT,STI,ZION,,
7	MARSHALL & ILSLEY	0.65*	MMC,TMK
8	MARSH & MCLENNAN	0.63*	MI,NTRS,PGR,SEIC,TROW,UNM
9	MORGAN STANLEY	0.62*	AIG,AON,BAC,EV,GS,HBAN,HCBK,MTB,SCHW,SEIC,STT
10	AMERICAN INTL.GP.	0.61*	FRE,MBI,RF,TMK
11	PROGRESSIVE OHIO	0.58*	AFL,ALL,NTRS,WRB
12	STATE STREET	0.55*	AXP,NTRS
13	ZIONS BANCORP	0.51*	BBT,CMA,HBAN,MTB,PNC,RF,STI,
14	FIFTH THIRD BANCORP	0.49*	AON,LUK,RF,SLM,SNV,STI,WFC,ZION
15	NY.CMTY.BANC.	0.49	PBCT,WFC
16	PNC FINANCIAL SVS. GP	0.47*	BAC,CMA,STT,TMK,WFC,ZION
17	FANNIE MAE	0.45*	AIG,FRE
18	FRANKLIN RESOURCES	0.34*	AON,AXP,BBT,EV,GS,LM,MBI,NTRS,SLM,SNV,TROW
19	CHARLES SCHWAB	0.33*	AMTD,GS,JPM,NTRS,TROW
20	CHUBB	0.30*	AFL,L,LNC,PBCT,PGR
21	WELLS FARGO & CO	0.28*	BAC,BBT,CB,LNC,MTB,NYB,STI
22	FREDDIE MAC	0.19*	BBT,EV,FITB,FNM,LUK
23	HARTFORD FINL.SVS.GP.	0.19*	CB,L,LNC,MI,NTRS,TMK
24	CINCINNATI FINL.	0.16*	CB,MBI,STI
25	TORCHMARK	0.12*	AFL,ALL,BBT,HIG,LNC,NTRS,SEIC,UNM,UNP,
26	UNUM GROUP	0.04*	AFL,ALL,L,LNC,MMC,STI

Table 6: Rankings of relevant systemic risk contributions based on estimated realized systemic risk betas $\widehat{\widetilde{\beta}}_t^{s|i}$ at the specific point in time. Estimated systemic risk betas and VaRs are listed in addition illustrating the different sources of variation in $\widehat{\widetilde{\beta}}_t^{s|i}$. Systemic risk contributions based on time-varying betas are marked by *.

a) End of March 2007 (before the beginning of the financial crisis)

Rank	Name	$\widehat{\widetilde{\beta}}_{2007}^{s\|i} \cdot 10^2$	$\hat{\beta}_{2007}^{s\|i}$	$\widehat{VaR}_{2007}^{i}$
1	CITIGROUP	**1.78***	0.263	0.068
2	AMERICAN EXPRESS	**1.35***	0.387	0.035
3	BANK OF AMERICA	**1.16***	0.304	0.038
4	JP MORGAN CHASE & CO.	**1.05**	0.265	0.040
5	MORGAN STANLEY	**1.01***	0.146	0.069
6	LEGG MASON	**0.98***	0.205	0.048
7	MARSH & MCLENNAN	**0.83***	0.222	0.037
8	REGIONS FINANCIAL	**0.78***	0.202	0.038
9	PNC FINANCIAL SVS. GP	**0.77***	0.248	0.031
10	CHUBB	**0.74***	0.240	0.031
11	AMERICAN INTL.GP.	**0.61***	0.143	0.043
12	FRANKLIN RESOURCES	**0.60***	0.143	0.042
13	STATE STREET	**0.51***	0.114	0.045
14	FIFTH THIRD BANCORP	**0.50***	0.104	0.048
15	PROGRESSIVE OHIO	**0.42***	0.092	0.046
16	NY.CMTY.BANC.	**0.41**	0.090	0.045
17	MARSHALL & ILSLEY	**0.40***	0.088	0.045
18	TORCHMARK	**0.39***	0.173	0.023
19	HARTFORD FINL.SVS.GP.	**0.38***	0.099	0.039
20	ZIONS BANCORP.	**0.26***	0.115	0.054
21	CHARLES SCHWAB	**0.25***	0.042	0.060
22	FREDDIE MAC	**0.23***	0.057	0.041
23	LEUCADIA NATIONAL	**0.19***	0.057	0.033
24	CINCINNATI FINL.	**0.13***	0.026	0.050
25	FANNIE MAE	**0.09***	0.019	0.049
26	UNUM GROUP	**0.23***	0.045	0.051
27	T ROWE PRICE GP.	**0.06***	0.014	0.043
28	LINCOLN NAT.	**0.04***	0.010	0.036

b) End of June 2008 (during the financial crisis)

Rank	Name	$\widehat{\widetilde{\beta}}_{2008}^{s\|i} \cdot 10^2$	$\hat{\beta}_{2008}^{s\|i}$	$\widehat{VaR}_{2008}^{i}$
1	BANK OF AMERICA	**2.86***	0.186	0.154
2	AMERICAN EXPRESS	**2.78***	0.278	0.100
3	WELLS FARGO & CO	**2.51***	0.186	0.135
4	MARSHALL & ILSLEY	**2.31***	0.516	0.045
5	JP MORGAN CHASE & CO.	**2.22**	0.265	0.084
6	PROGRESSIVE OHIO	**1.97***	0.380	0.052
7	LEGG MASON	**1.96***	0.137	0.143
8	REGIONS FINANCIAL	**1.86***	0.107	0.173
9	MARSH & MCLENNAN	**1.76***	0.471	0.037
10	STATE STREET	**1.44***	0.171	0.084
11	NY.CMTY.BANC.	**1.12**	0.090	0.125
12	PNC FINANCIAL SVS. GP	**1.09***	0.153	0.071
13	CHUBB	**1.07***	0.176	0.061
14	TORCHMARK	**1.00***	0.177	0.057
15	CHARLES SCHWAB	**0.91***	0.149	0.060
16	CITIGROUP	**0.90***	0.072	0.124
17	MORGAN STANLEY	**0.61***	0.074	0.083
18	ZIONS BANCORP.	**0.58***	0.058	0.100
19	UNUM GROUP	**0.34***	0.033	0.104
20	UNION PACIFIC	**0.27***	0.047	0.056
21	HARTFORD FINL.SVS.GP.	**0.24***	0.012	0.201
22	FRANKLIN RESOURCES	**0.17***	0.026	0.064
23	T ROWE PRICE GP.	**0.01***	0.001	0.102

Table 7: Group ranking of systemic risk contributions for the pre-crisis period 2000 - mid 2007. The upper part, group 1 ('high'), contains companies with significant $\beta_t^{s|i}$ and the highest quartile of significant betas: $\hat{\bar{\beta}}_{av}^{s|i} \cdot 100 \in [0.5, 1.3]$. Group 2 refers to the third quartile ('medium') with $\hat{\bar{\beta}}_{av}^{s|i} \cdot 100 \in [0.03, 0.49]$ and Group 3 to realized systemic risk betas lower than the median value ('small'), for which $\hat{\bar{\beta}}_{av}^{s|i} \cdot 100 < 0.01$. Group 4 includes companies not determined to be systemically risky during the estimation period, i.e., those with insignificant systemic risk betas. Case study companies are marked in bold.

Systemic risk contributions	Companies
Group 1 'high'	**AIG**, **LEH**, MS, JPM, GS,STT, CINF, LM, PBCT
Group 2 'medium'	**FRE**, **ML**, BAC, C, RF, AXP, PNC,CNA, TROW, NTRS
Group 3 'low'	FNM, WFC, EV, TMK, BBT, AFL, HUM, MI, CMA, BK, LNC, ALL, HNT, CB, CVH, SLM, ETFC
Group 4	AMTD, AON, BEN, CI, FITB, HBAN, HCBK, HIG, L, LUK, MBI, MMC, MTB, NYB, PGR, SCHW, SEIC, SNV, STI, UNM, UNP, WRB, ZION

Table 8: Summary of estimation and test results for the four case study companies: loss exceedances influencing each company's VaR, the most important other VaRs influenced, joint significance tests on $\beta_t^{s|i} = 0$ and estimated average systemic risk contributions and betas. Estimation period: January 2000 - June 2007.

Name	incluenced by	main influences	overall sign.	average $\hat{\bar{\beta}}_t^{s|i} \cdot 100$	average $\widehat{\beta}_t^{s|i}$
FREDDIE	AON, BBT, EV, FITB, FNM, HUM, MBI	BBT, FNM	0.048	0.38	0.092*
MERRILL	AMTD, CB, CNA, HCBK, L, NYB, WRB	C	0.051	0.03	0.030*
LEHMAN	AMTD, AON, BEN, GS, JPM, LM, LUK, MI, MS	AIG, AXP, ETFC, JPM	0.041	0.79	0.176*
AIG	ALL, C, CB, CNA, ETFC, HIG, LEH, LNC, MBI, MMC, SCHW, STT, TMK	AFL, C, CNA, HIG, HUM, MMC, UNM	0.026	0.73	0.210*

* time-varying betas

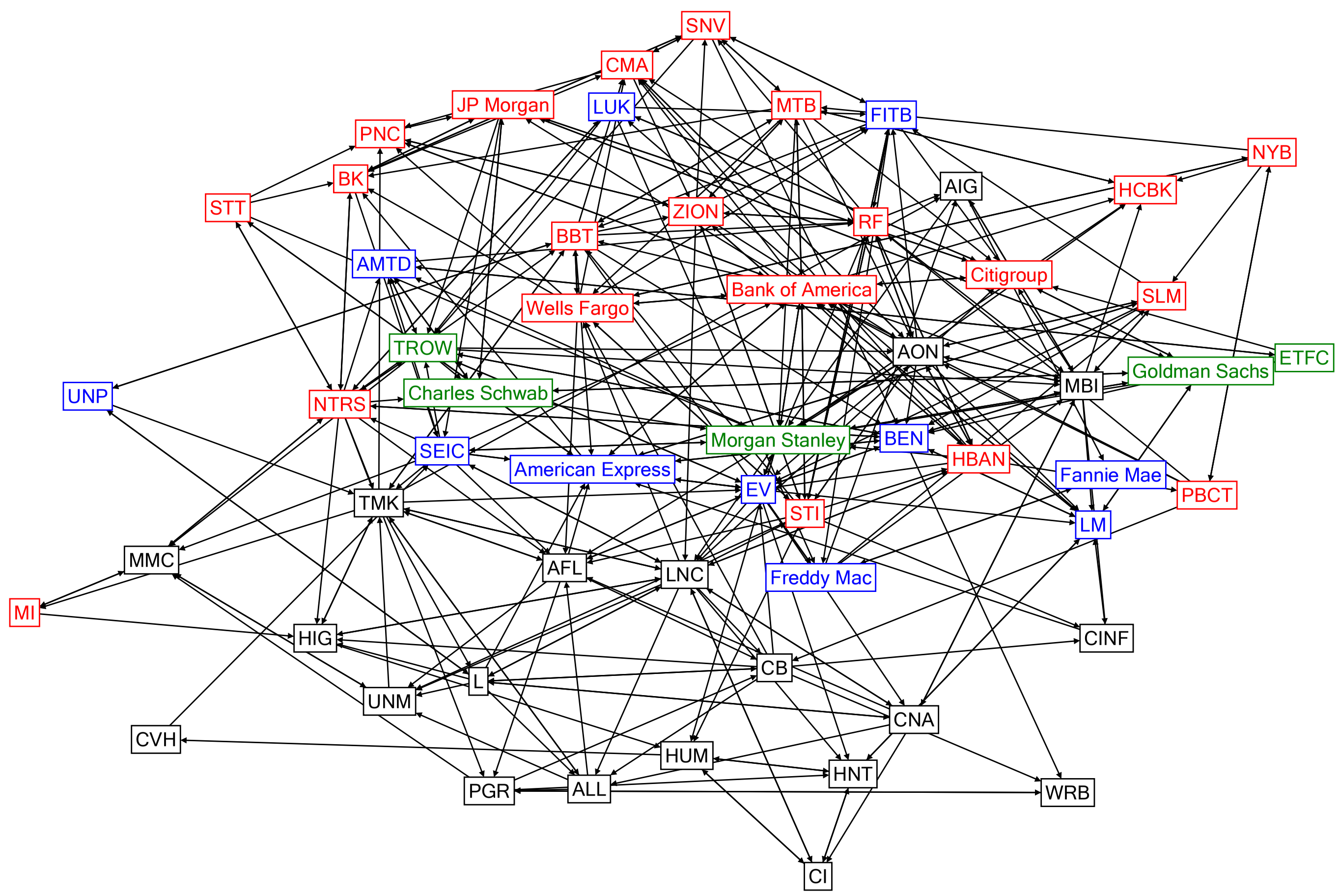

Figure 5: Full network graph for the system of the 57 largest financial companies in the U.S. For simplicity, arrows only mark risk spillovers effects without referring to their respective size. Otherwise arrows and colors are as defined in Figure 1. A complete list of firms' acronyms is contained in Table 1. The graphical allocation is obtained via the Fruchtermann-Reingold algorithm which minimizes the total length of all arrows.

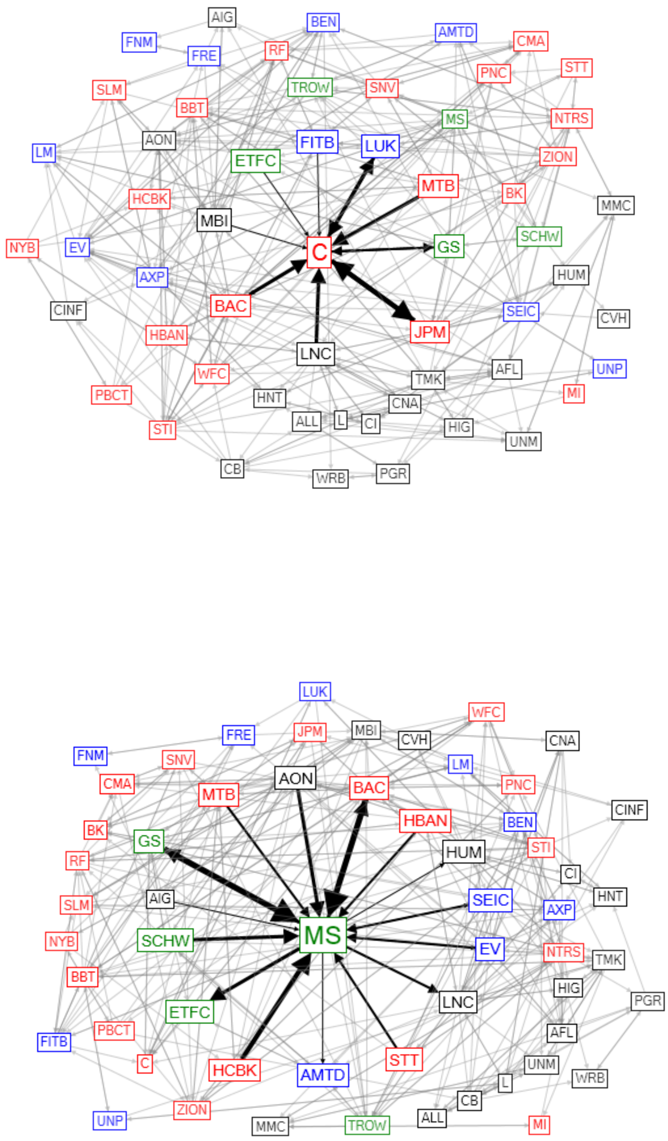

Figure 6: Full Network graphs of Citigroup (C) and Morgan Stanley (MS) highlighting risk drivers and risk recipients directly connected to the respective companies with bold arrows according to the respective size of the effect. Arrows, colors and acronyms are as in Figure 5. For simplicity, all other links just mark spillover effects without referring to size. The list of firm acronyms is contained in Table 1.

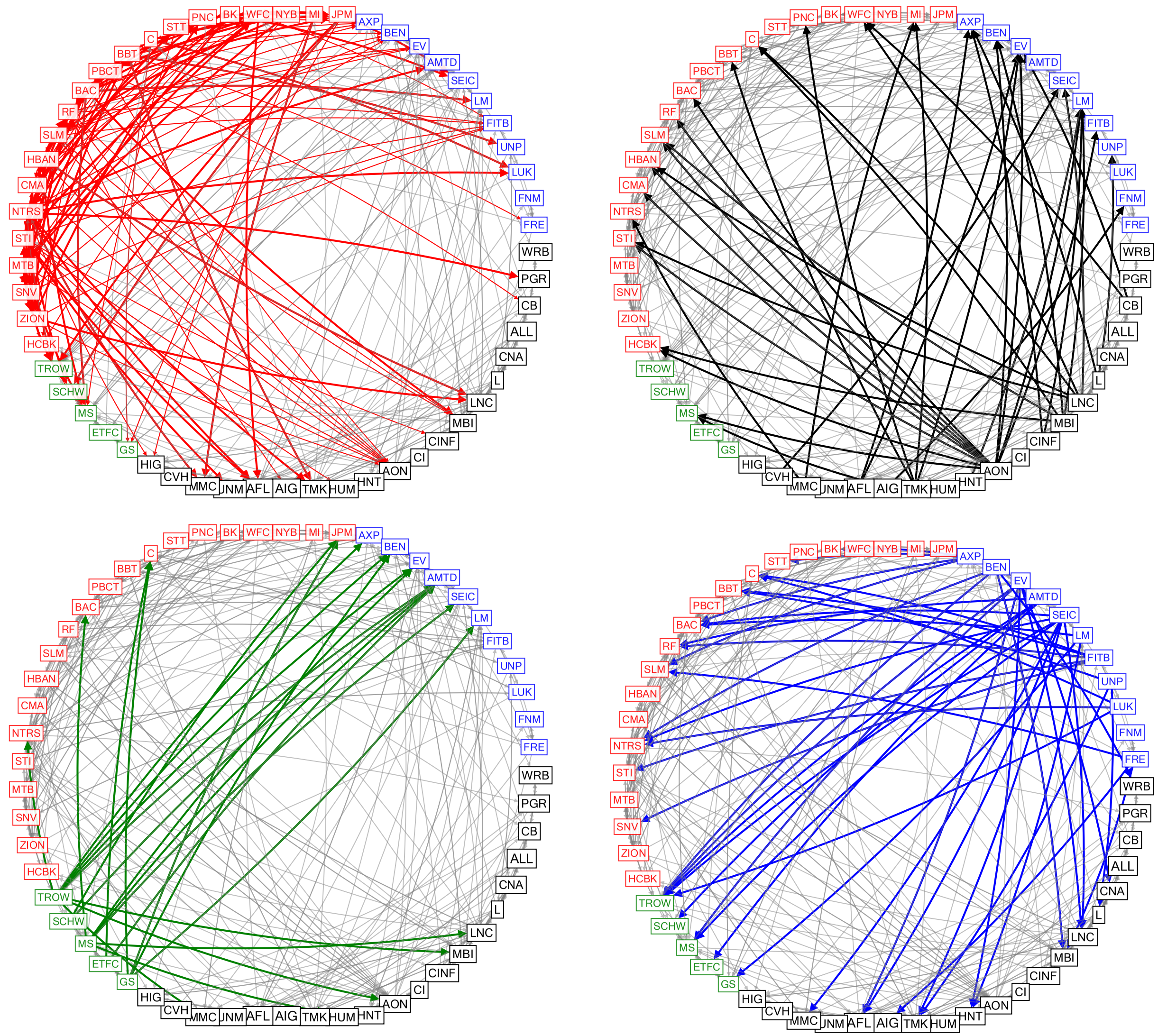

Figure 7: Network graph arranged according to industry groups highlighting the industry-specific risk spillovers from depositories (top left), insurances (top right), broker dealers (bottom left) and others (bottom right). Arrows only mark risk spillovers effects without referring to their respective size. Otherwise arrows and colors are as defined in Figure 1. A complete list of firms' acronyms is contained in Table 1 in the Appendix.

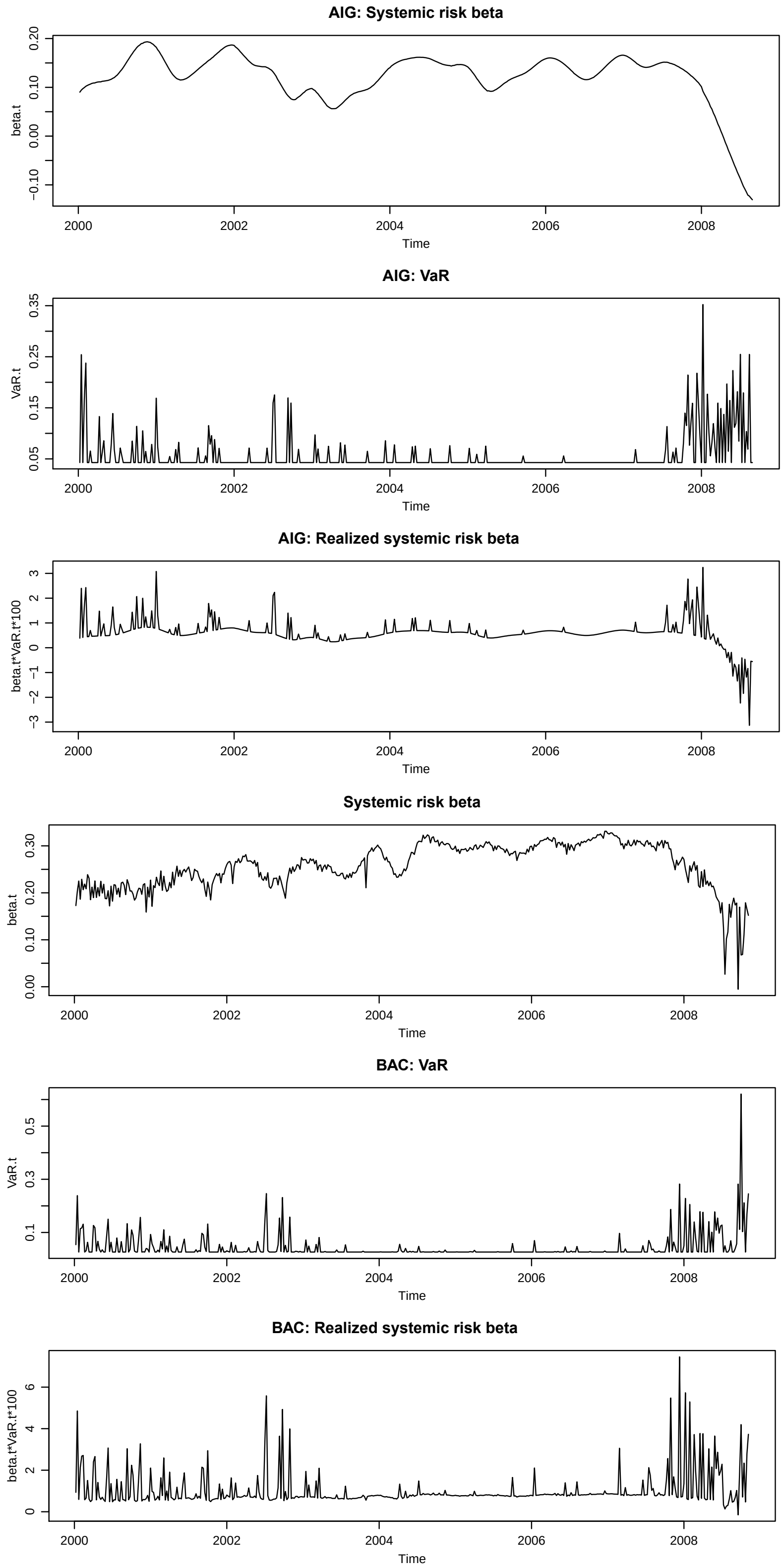

Figure 8: The upper three panels depict time-varying systemic risk beta's, time-varying VaRs and the product of the two, realized systemic risk beta's, for American International Group (AIG). The lower three panels show the respective three time series for Bank of America (BAC).

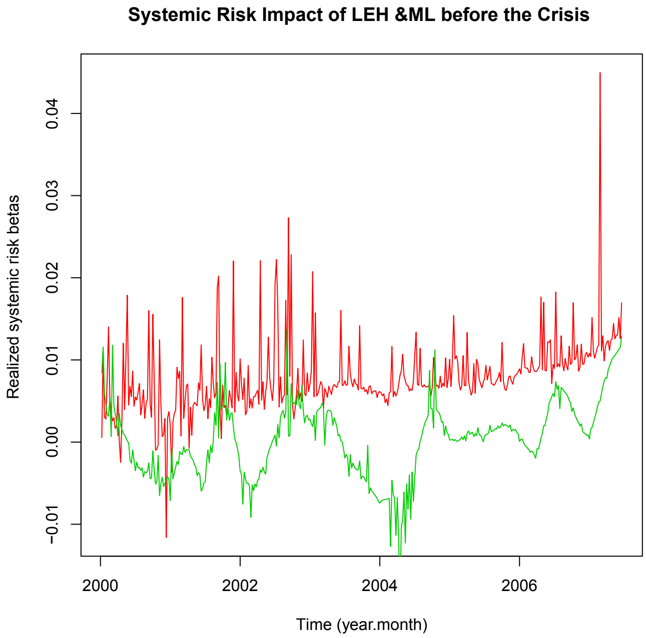

Figure 9: Realized systemic risk betas, i.e., the products of estimated systemic risk betas and individual VaRs, of Lehman Brothers (LEH, red) and Merrill Lynch (ML, green). Estimation period is the pre-crisis period, 2000 - mid 2007.

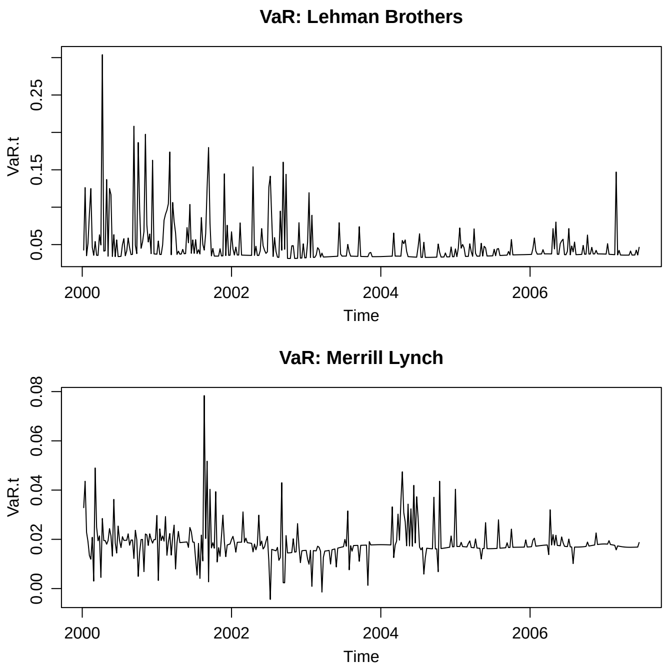

Figure 10: Estimated company-specific VaRs of Lehman Brothers (upper panel) and Merrill Lynch (lower panel). Estimation period is the pre-crisis period, 2000 - mid 2007.

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