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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 as well as 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. 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 supervision.

Keywords: Time-varying systemic risk contribution, systemic risk network, network topology estimation, Value at Risk

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

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1. Introduction

The financial crisis 2007-2009 has shown that cross-sectional dependencies between assets and credit exposures can cause 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. Moreover, there is an apparent need for respective empirically feasible 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 supervision authorities 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 compa-

[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".

nies' 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 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 banking supervisors 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. Our measure quantifies the risk of distress of individual companies and the entire system according to the tails of the corresponding asset return distributions, and is thus based on respective extreme conditional quantiles. In this sense, it 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

[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.

firm's position within the financial network as well as overall market conditions. [5] 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.

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 identifying 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 estimate the VaR of a value-weighted index of the financial sector as function of 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 as systemically relevant if the marginal effect of its individual VaR on the VaR of the system is detected as statistically significant. In analogy to an

[5] Note that we focus our analysis on dependencies of extreme tail risks to evaluate the systemic impact of the riskiness of a specific firm. Though the presented econometric methodology is readily extendable to also detect system tail risk consequences from non-extreme individual shocks by including individual VaR's around e.g. the 25% or even closer to the 50% level.

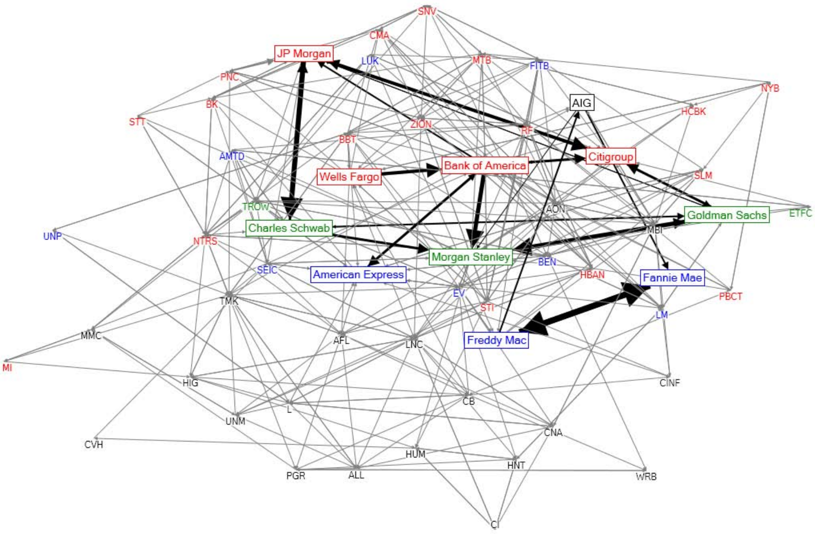

Figure 1: Risk network of the U.S. financial system schematically highlighting key companies in the system in 2000-2008. Details on all other firms in the system only appearing as unlabeled shaded nodes will be provided later in the paper. Depositories are marked in red, broker dealers in green, insurance companies in black, and 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.

(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 degree of systemic importance 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 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.

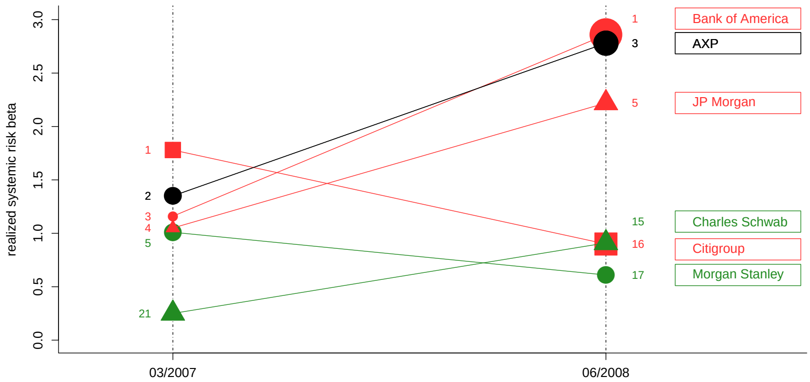

Figure 2: Systemic importance of five exemplary firms in the U.S. financial system at two time points before and at the height of the financial crisis, 2008. Systemic relevance is determined by the statistical significance and positivity of "systemic risk betas" quantifying the marginal increase of the 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 the degree of systemic relevance by the size of 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 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 times the 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.

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 can to a large part be attributed to direct credit or liquidity exposures, but in some cases especially for mutual effects, they might also result from common, e.g., sector or business model specific factors, not covered by the fundamental firm specific controls in the model. In any case, these links 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 receive and transmit tail risk. From a supervisory 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. The highest attention of supervision authorities should be attracted by firms which mainly appear 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.

The remainder of the paper is structured as follows. Section 2 describes the paper's link to related literature and presents the underlying data. In Section 3, we present the model and estimation procedure for individual companies' VaRs which are the basis for determining the systemic tail-risk network structure. The realized systemic risk beta is formally introduced in Section 4 and is identified for each firm in an individually tailored parsimonious partial equilibrium setting. The section also contains the corresponding estimation procedure and valid inference for a two-step quantile regression setting. Empirical results are presented in form of systemic risk rankings. In Section 5, we robustify and validate our model and results. In particular, in a case study using only pre-crisis data, we illustrate that the realized systemic risk beta works well in predicting the distress and systemic relevance of five large financial institutions that were affected by the financial crisis. Section 6 concludes.

2. Literature and data

2.1. Relation to the recent empirical literature

Our paper relates to several strands of recent empirical literature on systemic risk contributions. Building on VaR, Adrian and Brunnermeier (2011) were the first to model systemic risk contributions based on balance sheet characteristics. Their systemic impact measure, $\Delta CoVaR$, builds on deviations of a firm's CoVaR from a respective median benchmark. While CoVaR also aims at measuring the impact of a firm's individual risk on the system VaR, there are, however, substantial conceptional differences to our realized systemic risk beta: The latter is the direct marginal effect of the individual VaR on the VaR of the system, while for CoVaR, the respective marginal effect is determined from the return and only evaluated at the VaR. As returns are in $(1-q)\%$ of the time below its VaR(q)[6], the corresponding estimated coefficient of marginal systemic importance of CoVaR is generally larger and tends to systematically overrate firms with lower average returns for identical risk levels in contrast to the systemic risk beta. Furthermore, CoVaR can by definition only vary over time through the channel of individual VaRs which can, however, due to multicollinearity effects, solely be modeled as functions of macroeconomic market variables. Consequently, changes in a firm's systemic relevance in CoVaR ultimately only result from variations in underlying macroeconomic indicators. Thus, particularly variations in a firm's leverage or maturity mismatch as well as in its interdependence with other institutions have no direct effect. Instead, we account for network interconnections in the individual VaR and in its effect on the system. In addition, we identify network spillovers as crucial elements for measuring individual risk and for unbiased estimation of systemic relevance. This is illustrated in a robustness study in Subsection 3.3.1. Moreover, our realized systemic risk beta also captures variations in firms' marginal systemic importance driven by changes in firm-specific characteristics.

Our work also complements papers measuring a company's systemic relevance in terms of the size of potential bail-out costs, such as Acharya, Pedersen, Philippon, and Richardson (2010), Brownlees and Engle (2012) and Acharya, Engle, and Richardson (2012). Such approaches cannot detect spillover effects driven by the topology of the risk network and might tend to under-estimate the systemic importance of very interconnected companies. Moreover, while Brownlees and Engle (2012) study the situation of an individual firm given distress of the system, we investigate the reverse relation and measure the effect on the system given an individual firm is in financial trouble. Taking complementary perspectives, both approaches measure different dimensions of systemic risk. However, as our model is based on economic state variables and loss exceedances, it 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) and empirically results in realized systemic risk betas indicating the raise in systemic relevance of some

[6]The VaR(q) is defined as the negative q-conditional return quantile.

companies earlier than in competing settings. We illustrate these effects in the validity case study in Section 5.2.

Furthermore, our work also complements and augments research of Billio, Getmansky, Lo, and Pelizzon (2012) who present a collection of different systemic risk measures. These approaches mainly build on regressions in (conditional) means of returns. However, assessing and predicting systemic risk and firm-specific risk requires regression approaches in the (left) tails of asset return distributions, rather than in the center. Thus we quantify extreme tail situations of financial distress, which is in clear contrast to a correlation type analysis as in Billio, Getmansky, Lo, and Pelizzon (2012). Moreover, their determination of causality and resulting network links is entirely based on pairwise relations. This approach produces misleading results in a high-dimensional interconnected system as it is impossible to identify whether one firm drives another or if they are both driven by a third company. Instead, our approach yields consistent results for a multivariate tail-risk network, while satisfying the Granger-causality argument in quantiles through optimal backtest performance in overall fit. Our results are also complementary to network analysis focusing on volatility spillovers in vector autoregressive systems such as in Diebold and Yilmaz (2012) and Diebold and Yilmaz (2013).

Finally, we complement macroeconomic approaches which have 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).

2.2. 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.[7] To assess a firm's systemic relevance, we use publicly acces-

[7]Companies are classified into these groups according to their two-digit SIC codes, following the categorization in Adrian and Brunnermeier (2011), Appendix C.

sible market and balance sheet data. In particular, the forward-looking nature and real-time availability of equity market data serves well to provide an immediate, actionable and transparent measure of systemic risk. The advantage of timeliness will even prevail if new financial regulation might force institutions to reveal information on mutual credit and liquidity linkages and leverage to supervisory authorities. At the moment, data on connections between firms' assets and obligations is largely proprietary and far from comprehensive even for supervisors.

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 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).[8]

Moreover, to capture characteristics of individual institutions predicting a bank's propensity to become financially distressed, $\boldsymbol{C}^i_{t-1}$, 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-

[8]We found that this set of aggregate financial market variables provides sufficient explanatory power which cannot be augmented by additional controls such as, e.g., Fama-French type factors (see Subsection 3.3.1 for details).

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.[9]

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.[10] 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 excludes companies which defaulted during the financial crisis, but which are addressed separately in a shorter sample case study. Thus in order 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.

3. A tail risk network

3.1. Determining drivers of firm-specific tail risk

We measure the tail risk of a company with asset return X_t^i at time t as its conditional Value-at-Risk (VaR), $VaR_{q,t}^i$, given a set of company-specific tail risk drivers $\mathbf{W}_t^{(i)}$

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

[9]See Adrian and Brunnermeier (2011), Appendix C, who explicitly show that this induces no inherent endogeneity in the model.

[10]For in-sample estimation this interpolation step captures changes in balance sheet characteristics in a smoother way than the use of plain data. For forecasting purposes, however, interpolation is not possible. See Hautsch, Schaumburg, and Schienle (2013) for details.

with $VaR^i_{q,t} = VaR^i_{q,t}(\mathbf{W}^{(i)}_t) = -Q^i_{q,t}$ denoting the (negative) conditional q-quantile of X^i_t.[11] The *relevant* i-specific tail risk drivers are determined out of a large set of potential regressors $\mathbf{W}_t$ containing lagged macroeconomic state variables $\mathbf{M}_{t-1}$, lagged firm-specific characteristics $\mathbf{C}^i_{t-1}$, the i-specific lagged return X^i_{t-1}, and influences of all other companies apart from i, $\mathbf{E}^{-i}_t = (E^j_t)_{j \neq i}$. We capture these intra-system influences via contemporaneous loss exceedances, where the loss exceedance of a firm j is defined as $E^j_t = X^j_t \mathbf{1}(X^j_t \leq \hat{Q}^j_{0.1})$ 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.

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

$$VaR^i_q = \mathbf{W}^{(i)\prime} \boldsymbol{\xi}^i_q \,. \tag{2}$$

This could be estimated from a corresponding linear model in the respective return quantile

$$X^i_t = -\mathbf{W}^{(i)\prime}_t \boldsymbol{\xi}^i_q + \varepsilon^i_t, \quad \text{with} \quad Q_q(\varepsilon^i_t | \mathbf{W}^{(i)}_t) = 0 \tag{3}$$

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

$$\frac{1}{T} \sum_{t=1}^{T} \rho_q \left(X^i_t + \mathbf{W}^{(i)\prime}_t \boldsymbol{\xi}^i_q \right) \tag{4}$$

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

$$\widehat{VaR}^i_{q,t} = \mathbf{W}^{(i)\prime}_t \widehat{\boldsymbol{\xi}}^i_q \,. \tag{5}$$

However, the relevant risk drivers $\mathbf{W}^{(i)}$ for firm i are unknown and must be determined from $\mathbf{W}$ in advance. This model selection should not be imposed but should be data-

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

driven. Appropriate econometric techniques are 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. 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,

$$\widetilde{\boldsymbol{\xi}}_q^i = \text{argmin}_{\boldsymbol{\xi}^i} \frac{1}{T} \sum_{t=1}^{T} \rho_q \left(X_t^i + \mathbf{W}_t' \boldsymbol{\xi}^i \right) + \lambda^i \frac{\sqrt{q(1-q)}}{T} \sum_{k=1}^{K} \hat{\sigma}_k |\xi_k^i| \ , \tag{6}$$

with the set of potentially relevant regressors $\mathbf{W}_t = (W_{t,k})_{k=1}^K$, which are demeaned, componentwise variation $\hat{\sigma}_k^2 = \frac{1}{T} \sum_{t=1}^T (W_{t,k})^2$ and the loss function ρ_q as in (4). 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 (6). 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 (6), all coefficients $\widetilde{\boldsymbol{\xi}}_q^i$ are generally downward biased in finite samples. Therefore, we re-estimate the unrestricted model (4) only with the selected relevant regressors $\mathbf{W}^{(i)}$ yielding the final estimates $\widehat{\boldsymbol{\xi}}_q^i$. This post-LASSO step produces finite sample estimates of coefficients $\boldsymbol{\xi}_q^i$ 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 the consistency proof 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 is chosen, the more regressors are eliminated. Conversely, in case of $\lambda^i = 0$, we are back in the standard quantile regression setting (4) 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 respective measure of noise in the sample criterion function. In particular, we use the supremum norm of a rescaled gradient of the sample criterion function evaluated at the true parameter value as in Belloni and Chernozhukov (2011)[12]. 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 further 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, for instance, 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 ensures that VaR violations today do not contain information about VaR violations in the future and both occur according to the same distribution. The respective formal test uses 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 (2011) 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)).

We estimate VaR specifications with $q = 0.05$ for all companies employing the LASSO selection procedure described above.[13] Exemplary VaR^i (post-)LASSO regression re-

[12]See Appendix A.2 Step 1 for the scaling and the exact formula.

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

sults for firms in the four industrial sectors depositories, insurances, brokers and others are provided in Table 2. It turns out that the main relevant 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 from other firms. The general importance of cross-firm effects as main drivers of individual tail risks is confirmed by joint significance test of the individually selected loss exceedances $\mathbf{E}_t^{-i}$ and by the superior VaR forecast performance. Please see the robustness Subsection 3.3 for details.

With our procedure we statistically detect "relevant" directional risk connections in the financial sector. Certainly, there might be several types of economic causes for a link between two companies which can, however, empirically not be further identified from publicly disclosed market data.[14] By including firm-specific characteristics and macroeconomic state variables in our model, we do prevent, however, that determined risk connections result from common economic conditions or common risk factors. Hence, we rule out that tail dependencies are driven, for instance, by periods of high volatility, flattening of yield curves or falling overall credit quality. Accordingly, risk links are attributed to remaining factors which are most likely direct or indirect credit or liquidity exposures or, in some cases, business model commonalities or sector specific risk factors. In this sense, connections between close competitors, such as Goldman Sachs and Morgan Stanley and the influence of mortgage company Freddie Mac (FRE) on AIG both confirm market evidence.

[14]Note that a valid empirical classification into different types of linkages would require comprehensive data on direct and indirect credit and liquidity exposures of firms. Such information, however, is in large part not publicly available.

3.2. Network model and structure

We constitute a tail risk network of the system from individually selected loss exceedances reflecting cross-firm dependencies.[15] 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 (6) 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 network arrow from firm j to firm i.

As in the previous subsection, we use VaR specifications with $q = 0.05$. 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 interconnected 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 6. The layout and allocation of the network is chosen such that the sum of cross-firm distances is minimized. Consequently, the most connected firms are located in the center of the network while the less involved companies are placed on 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 dis-

[15] In the Bayesian network literature, networks which build on direct one-step influences constitute a so-called Markov blanket assumed to contain all relevant information for predicting the node's role in the network (see Friedman, Geiger, and Goldszmidt, 1997).

tress of other firms. They should be the focus of close monitoring by supervisory authorities as a failure of such a company might induce substantial systemic risk 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 influences 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 6 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 amplifying 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 focus of supervision authorities should be on a close monitoring of the first subgroup. 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 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 7. Morgan Stanley, with strong links to many companies, such as Goldman Sachs, Bank of America, 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, a close and detailed 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 8 indicates 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.

3.3. Robustness

3.3.1. Network model validity

Given our data set, it is sensible to base our tail-risk networks on VaR levels of $q = 5\%$. More extreme probabilities are theoretically feasible but require a larger amount of observations for sufficient statistical precision. We have also experimented with different thresholds in the loss exceedances but found that for the present data, the 10% quantile optimally balances the trade-off between requiring sufficient number of nonzero observations in $\mathbf{E}_t^{-i}$ and a sufficient number of extreme losses.

The significance of network effects in the individual VaR specifications can be formally tested via a joint significance test of the individually selected loss exceedances $\mathbf{E}_t^{-i}$ in the respective quantile regression (2). We have performed this analysis based on a quantile regression version of the F-test for joint linear hypotheses developed by Koenker and Bassett (1982). Our results show 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 detailed test results are available upon request.

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 (in-sample) forecast performance of our LASSO-selected VaR specifications to corresponding models for 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

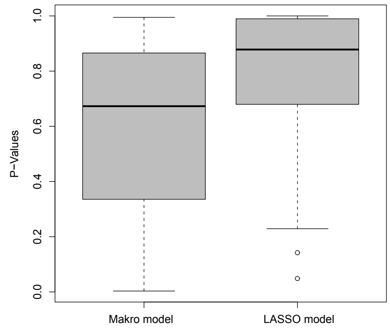

Figure 3: Boxplots of backtesting p-values indicating the in-sample model fit (i.e., testing the null hypothesis of formal statistical adequacy) of VaR specifications including macroeconomic regressors only (left) and VaR specifications resulting from the LASSO selection procedure (6) (right).

strong predictive ability and are significantly superior to more simplistic models including macroeconomic regressors only (and ignoring network linkages). Figure 3 illustrates the distributions of the backtesting p-values implied by both models. Hence, inter-company linkages add crucial explanatory power in VaR specifications.

Network effects also remain important when altering the set of economic state variables $\mathbf{M}$ by typical equity risk premium factors. In particular, we re-estimated the model including four lagged weekly asset pricing factors, including the three Fama-French factors and the momentum factor according to Carhart (1997).[16] However, in the presence of network exceedances, these factors have been de-selected in all cases by the LASSO method and thus have had no additional relevance for our model specification. This indicates that the tails of asset returns are driven by other sources than the equity risk premium (associated with return's conditional mean).

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 contemporaneous returns X_t^{-j} or lagged loss exceedances $\mathbf{E}_{t-1}^{-i}$ imply significantly inferior backtest performances with the regressors be-

[16]The data are downloaded from the website of Kenneth French on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

ing mostly not significant in joint F-tests.[17] 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.[18]

3.3.2. Accuracy of the LASSO selection step

The firm-specific LASSO penalty parameter λ^i is a crucial parameter in our approach as it determines the denseness of the risk network, and also influences the outcomes from the second stage systemic risk measure in Section 4. It is chosen in a completely data-driven procedure, such that a backtest criterion is optimized (see Sections 3.1 and A.2). To validate this model selection step and to assess whether the procedure prevents overfitting, we analyze the consequences of increasing the LASSO penalty parameter. Note that higher values of λ^i lead to selections of smaller models. If our procedure had a tendency to overfit the tails, the overall goodness of fit would increase for higher values of λ^i. This possibility is checked by increasing all penalty parameters by 10% and 20%, and analyzing two different measures of fit for the resulting models.[19] Firstly, according to our backtest

[17]The corresponding results are available upon request and omitted here for sake of brevity.

[18]Econometrically it is an open question 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 structures (see White, Kim, and Manganelli (2010)).

[19]It turns out that increasing the penalties beyond 20% is not advisable as for a number of VaRs, no regressors are selected anymore.

criterion, the overall goodness of fit deteriorates substantially, which is demonstrated by three boxplots and exemplary illustrations of individual p-values shown in Figure 12. It turns out that for higher values of λ^i, the p-values decrease and thus the statistical support for the null hypothesis of a good model fit declines. Likewise, joint significance tests do not support the exclusion of additional regressors due to higher penalties. In particular, it turns out that the additionally de-selected regressors are mostly significant (jointly with the selected ones). This finding is further robustified by a second goodness of fit measure corresponding to a Bayesian Information Criterion (BIC) for quantile models proposed by Lee, Noh, and Park (2013). As shown by Figure 12, the BIC is increasing and thus indicates a less favorable model if the penalty parameter is increased. These evaluations support our choice of penalization and indicate that there is no evidence for a tendency of overfitting the tails.

3.3.3. Network characteristics

Besides graphical illustration and inflow-outflow categorizations, standard network characteristics can provide a more comprehensive picture of the interconnectedness and the role of each network 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.[20] Confirming the visual impression based on Figure 6, the most connected firms are Lincoln National Corporation, AON, Bank of America, TD Ameritrade and Morgan Stanley. The graph confirms our finding above that depositories tend to be slightly stronger involved than 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.

[20]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 be solved iteratively. For more details, see Berkhin (2005).

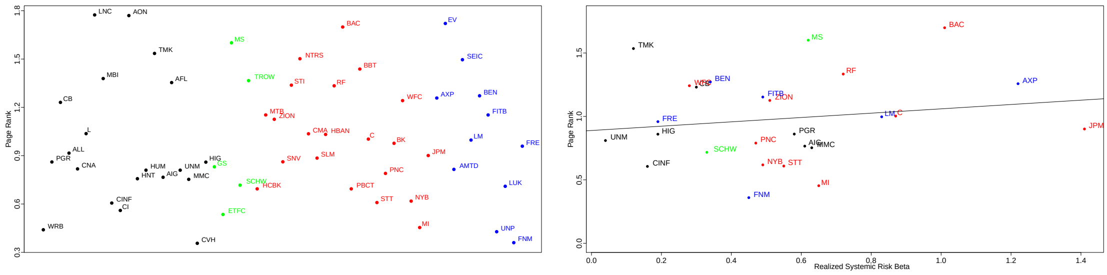

Figure 4: The left figure displays pagerank coefficients based on the estimated tail risk network computed as in Berkhin (2005) with ordering of institutions according to sectors. On the right, pagerank coefficients are plotted versus realized systemic risk contributions measured as average realized systemic risk betas (8) for all companies which are classified as systemically relevant for the years 2000-2008 according to Subsection 4.3. The regression line shows only a small correlation between the pagerank coefficent and the realized systemic risk beta, supported by the respective R^2 of 0.0265 of the regression. Colors and acronyms are as in Figure 1.

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 identifying 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.

4. Quantifying systemic risk contributions

4.1. Measuring and estimating systemic risk betas

Besides valuable information on financial network structures, the focus of supervision authorities is on an accurate but parsimonious measure of an institution's 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. As for firm's tail risk in equation (1), system tail risk is measured as the respective Value-at-Risk $VaR^s_{p,t}$ of the system return X^s_t conditional on $VaR^i_{q,t}$ and other controls. Then, we define the *systemic risk beta* as the marginal effect of firm i's tail risk on the system tail risk given by

$$\frac{\partial VaR^s_{p,t}(\mathbf{V}^{(i)}_t, VaR^i_{q,t})}{\partial VaR^i_{q,t}} = \beta^{s|i}_{p,q}, \tag{7}$$

where $\mathbf{V}^{(i)}_t$ are firm-specific control variables.[21] 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 system given network-specific effects and firm-specific and macroeconomic state variables. We classify the systemic relevance of institutions according to their statistical significance of $\beta^{s|i}_{p,q}$ at a given level and the size of their total effect

$$\bar{\beta}^{s|i}_{p,q} := \beta^{s|i}_{p,q} VaR^i_t \ , \tag{8}$$

which we denote as *realized* systemic risk contribution since it is computed based on market realizations. In contrast to the marginal systemic risk beta, the realized version captures the full partial effect of a tail risk increase of bank i on VaR^s_t and is thus cross-sectionally comparable across banks.

Focusing on an unbiased estimate of a firm's marginal effect, we employ for each company a tailored i-specific model for VaR^s in (7) which allows correctly evaluating the desired effect $\beta^{s|i}_{p,q}$. In particular, in each of this partial system VaR models, it is necessary but sufficient to control for firms which are relevant i-specific risk drivers in the network in VaR^s. Conversely, variables unrelated to VaR^i do not affect firm i's systemic risk contribution and can be omitted in a respective parsimonious model.[22] In this way, we circumvent involved theoretical specification issues and econometric feasibility and preci-

[21] Note that we only study the *immediate* effect of an exogenous risk shock in company i for the system. We do not infer about further steps which should then also account for converse effects of increases of system risk causing firm-specific risk to raise. This would require a further involved dynamic modeling step which is beyond the scope of this analysis.

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

sion problems of alternative comprehensive structural general equilibrium models. Even if correctly specified, such complete models would suffer from the high dimensionality and interconnectedness of the financial system in the presence of limited data availability. See Section 5 for an empirical comparison.

Consequently, we estimate the firm-i-specific *systemic risk beta* $\beta_{q,p}^{s|i}$ based on a linear model for the system VaR of the form

$$VaR_{p,t}^{s} = \mathbf{V}_t^{(i)\prime}\boldsymbol{\gamma}_p^{s} + \beta_{p,q}^{s|i} VaR_{q,t}^{i}, \tag{9}$$

where the vector of regressors $\mathbf{V}_t^{(i)} = (1, \mathbf{M}_{t-1}, \mathbf{VaR}_{q,t}^{(-i)})$ 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 3.

Systemic risk betas in (9) are moreover allowed to be explicitly time-varying, accounting for periods of turbulence where not only banks' risk exposures change but also their marginal importance for the system might vary. In particular, we model potential time-variation of $\beta^{s|i}$ through a linear model in observable factors $\mathbf{Z}^i$ which characterize a bank's propensity to get in financial distress. As a function of lagged characteristics, such *conditional* systemic risk betas and thus corresponding systemic risk rankings are predictable which is important for forward-looking monitoring and supervision of the financial system. Furthermore, linearity of $\beta_{p,q,t}^{s|i}$ in firm-specific distress indicators $\mathbf{Z}_{t-1}^{i}$ yields stable main effects, given the quarterly reporting frequency of these factors. The quality of generally available data limits the expected potential for improvements stemming from other functional forms or nonparametric estimates which would in any case substantially increase the statistical complexity and computational burden within the two-step model. Thus we set

$$\beta_{p,q,t}^{s|i} = \beta_{0,p,q}^{s|i} + \mathbf{Z}_{t-1}^{i}{}' \boldsymbol{\eta}_{p,q}^{s|i}, \tag{10}$$

where $\boldsymbol{\eta}_{p,q}^{s|i}$ are the parameters driving the time-varying effects.

The firm-specific time-varying systemic risk beta $\beta^{s|i}_{p,q,t}$ can then be estimated from the (second step) quantile model (9) for VaR^s_p with time variation according to (10). The respective quantile regression becomes operational when using post-LASSO pre-estimates $\widehat{VaR}^i_t$ and $\widehat{\mathbf{VaR}}^{(-i)}_{q,t}$ from (6) in the respective components of $\mathbf{V}^{(i)}$ for those regressors not directly observed in the data.[23] Hence,

$$X^s_t = -\beta^{s|i}_{0,p,q}\widehat{VaR}^i_{q,t} - (\widehat{VaR}^i_{q,t} \cdot \mathbf{Z}^i_{t-1})' \boldsymbol{\eta}^{s|i}_{p,q} - \widehat{\mathbf{V}^{(i)}}'_t \boldsymbol{\gamma}^s_p + \varepsilon^s_t, \tag{11}$$

where $Q_p(\varepsilon^s_t|\widehat{VaR}^i_{q,t}, \widehat{\mathbf{V}}^{(i)}_t, \mathbf{Z}^i_{t-1}) = 0$. Then, as in the first-step regressions in Section 3, estimates of all components of $\beta^{s|i}_{p,q,t}$ are obtained via quantile regression minimizing

$$\frac{1}{T}\sum_{t=1}^{T} \rho_p \left(X^s_t + \mathbf{V}'_t \boldsymbol{\xi}^s\right) \tag{12}$$

in the unknown parameters $\boldsymbol{\xi}^s$ where $\mathbf{B}_t \equiv (VaR^i_t, VaR^i_t \cdot \mathbf{Z}^i_{t-1}, \mathbf{V}^{(i)}_t)$ is the compound vector of all regressors in VaR^s_p. This yields the resulting estimate of the full time-varying marginal effect $\widehat{\beta}^{s|i}_{p,q}$ in (10),

$$\widehat{\beta}^{s|i}_{p,q,t} = \widehat{\beta}^{s|i}_{0,p,q} + \mathbf{Z}^i_{t-1}{}' \widehat{\boldsymbol{\eta}_{p,q}}^{s|i}, \tag{13}$$

for given values $\mathbf{Z}^i_{t-1}$. Constant systemic risk betas can obviously be obtained as a special case under the restriction $\boldsymbol{\eta}^{s|i}_{p,q} = 0$ in the estimation (12) yielding $\widehat{\beta}^{s|i}_{p,q,t} = \widehat{\beta}^{s|i}_{0,p,q} = \widehat{\beta}^{s|i}_{p,q}$. The realized beta (8) is estimated as $\widehat{\tilde{\beta}}^{s|i}_{p,q,t} := \widehat{\beta}^{s|i}_{p,q,t}\widehat{VaR}^i_t$.

For valid inference, however, the fact that certain regressors are not observed but only pre-estimated has crucial consequences. In particular, the quantile regression asymptotic standard errors of usual software packages based on Koenker and Bassett (1978) are gen-

[23] Note that a direct one-step plug-in version of the proposed two-step estimation strategy is not feasible and leads to an identification problem. Inserting the linear individual VaR (2) into the linear sytem VaR model (9) yields a full model for the system's tail risk in observable characteristics. But model selection based on such a full model for 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 and model selection step.

erally too small not accounting for the pre-step. In contrast to mean regressions, such two-step results are non-standard in a quantile setting and are therefore provided in detail in Appendix A.1. Up to our knowledge, they are new to the literature.

4.2. Determining systemic relevance

We determine systemic relevance and potential time variation thereof via formal statistical significance tests. Though, respective quantile versions of asymptotic t- or F-tests are not valid in finite samples and simple direct bootstrap adaptations yield incorrect results for quantiles.[24] Therefore, we propose to base a finite sample test for any linear hypothesis H of $\hat{\beta}^{s|i}_{p,q,t}$ on the type of test statistic statistic given by

$$S_T = \min_{\boldsymbol{\xi}^s \in \Omega} \sum_{t=1}^{T} \rho_p(X_t^s + \mathbf{B}_t' \boldsymbol{\xi}^s) - \min_{\boldsymbol{\xi}^s \in \mathbb{R}^{K_B}} \sum_{t=1}^{T} \rho_p(X_t^s + \mathbf{B}_t' \boldsymbol{\xi}^s), \tag{14}$$

with regressors $\mathbf{B}_t$ and corresponding K_B-parameter vector $\boldsymbol{\xi}^s$ as in the system VaR specification (12), and Ω referring to the constrained set of parameters of $\hat{\beta}^{s|i}_{p,q,t}$ under H. 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 14 involves unknown terms, and by the non-smooth objective function of the quantile regression causing inconsistency of conventional resampling techniques. Therefore, following Chen, Ying, Zhang, and Zhao (2008), we provide an adjusted "wild-type" bootstrap method, which is described in detail in Appendix A.4. We generally consider effects as being significant if p-values are below 10%.

We define a company as systemically relevant if an increase in its possible loss position, given all economic state variables and i-specific risk inflows from other companies,

[24] Generally, 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.

induces a significantly higher potential systemic loss. This requires its systemic risk beta to be significant *and* nonnegative.[25] The potentially time-varying degree of systemic relevance is then measured according to the size of its realized beta at the respective point in time. We can thus determine if a company is systemically relevant by testing for the significance of the respective systemic risk beta, which is the joint significance of all components of $\beta_t^{s|i}$. 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 H2 is not rejected, we re-specify the systemic risk beta as being constant ($\beta_t^{s|i} = \beta^{s|i}$), re-estimate the model without interaction variables and test the hypothesis **H3** : $\beta^{s|i} = 0$.

4.3. Empirical results and robustness of systemic risk betas and risk rankings

We estimate potentially time-varying systemic risk betas according to (12). 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 $p = q$. As potential drivers of time-variation in systemic risk betas, we take all firm-specific tail risk drivers, i.e., $\mathbf{Z}_t^i = \mathbf{C}_t^i$, since size, leverage, maturity mismatch, book-to-market ratio and volatility might not only affect a bank's VaR, but also directly

[25] 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 $\mathbf{Z}_{t-1}^i$. This stabilizes systemic risk betas but at the cost of a potentially high loss of information. We see this as an alternative approach which, however, is not pursued in the given context.

determine its marginal systemic effect. As a consequence, systemic risk contributions of two companies with the same exposure to macroeconomic risk factors and financial network spillovers may still differ due to their balance sheet structures.[26]

We find that the majority of firms have 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.[27] Table 5 lists all systemically relevant companies for the period from 2000 to 2008, ranked according to their average realized systemic risk contributions $\bar{\hat{\beta}}^{s|i}$. The top positions of the systemically most risky companies are taken by JP Morgan, American Express, Bank of America and Citigroup. According to our network analysis above, these firms are also categorized into the group of risk amplifiers which are strongly interconnected and should thus be closely monitored.

Obtained realized systemic risk betas, however, 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.

[26]Note that we keep the set of regressors M parsimonious as described in Section 2.2. According to Subsection 3.3.1) the increase in explanatory power stemming from additional factors such as, e.g., Fama-French/Carhart factors is low in the presence of network effects and thus can be neglected.

[27]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.

As a first rough validity benchmark of our assessment, 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. While we only rely on publicly available market data, the Fed could instead draw on extensive non-public confidential balance sheet information revealing credit- and other risk interconnection channels among the the 19 largest U.S. bank holding companies.[28] 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, we identify six out of eight banks contained in our database which, according to the SCAP results, were threatened by financial distress under more adverse market conditions.[29] 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 suggests that our method could also generally help supervisory agencies to respectively target the collection of detailed data beyond publicly available information within the entire banking system. For a more detailed validity study of the realized systemic risk beta, see the section below. We particularly refer to Subsection 5.2 presenting a pre-crisis case study which also provides direct comparisons to other empirical systemic risk contribution measures. Moreover, statistical robustness checks of an adapted realized systemic risk beta in a forecasting setting are provided in Hautsch, Schaumburg, and Schienle (2013).

While *average* systemic risk betas deliver a rough aggregated picture of systemic importance, the evolution of realized systemic risk betas over time provides additional company and sector date-specific information on systemic relevance which also incorporates

[28]For details on SCAP, see Federal Reserve System (2009). The Fed's measure for systemic relevance uses the proprietary information of risk interconnections within the system in order to determine requested individual capital buffers under different market scenarios. We relate the grouped results of the two network based measures along the following line of reasoning: As in Huang, Zhou, and Zhu (2010), companies with the highest detected systemic relevance in 2000-2008 should carry the highest share of hypothetical loss insurance premia and should thus also be found to face the highest requested increase in individual capital buffers in 2009.

[29]We detect Citigroup, FifthThird Bancorp, Morgan Stanley, PNC, Regions Financial and Wells Fargo as systemically relevant. 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.

market feedback. We focus on respective systemic risk rankings at two specifically illustrative 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 crisis rankings, we observe that generally systemic risk betas and thus the magnitude of systemic risk contributions significantly increased during the crisis. This is particularly pronounced for American Express, Bank of America, JP Morgan, Regions Financial and State Street. Exceptions are Citigroup and Morgan Stanley.

During the crisis, we detect Bank of America (BAC) as systemically most relevant. Among all systemically relevant companies, it is also the most interconnected firm according to the pagerank coefficient in Figure 4 mutually influencing and influenced by other companies in the center of the network as Morgan Stanley, American Express, Citigroup and Wells Fargo (see Table 3 and Figure 6). Figure 9 shows that BAC'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. Its realized systemic risk contribution, however, strongly increased during the crisis driven by the individual VaR channel which is determined entirely by corresponding network exceedances.[30] In this sense, the high systemic relevance of BAC can mainly be attributed to network effects. This is in contrast to AIG, where the systemic realized beta after its (anticipated) government-bailout from the beginning of 2008 is governed by a strong decline in its marginal systemic risk contribution (see Figure 9). Here, network effects entering through the increasing individual VaR, play a secondary role during this crisis period. We find that market data seem to incorporate bail-out information into the systemic risk beta well in advance to the actual government intervention in fall 2008.[31] In particular, the measured systemic relevance of AIG already rapidly declines from the beginning of 2008 on to the point where AIG is

[30]The detailed BAC results for the post-LASSO coefficients in Table 2 are omitted for the sake of brevity but are available on request.

[31]For details on the USD 150 billion rescue packages from the Federal Reserve, see Schich (2009).

no longer systemically important by the end of 2008. Thus both systemic risk beta and realized beta tend appear being forward-looking.

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 schematically depicted before and within the crisis in Figure 2 in the introduction. As for BAC, in many cases shown in Table 6, we observe increases of realized systemic risk contributions which are mainly due to rising individual VaRs, while companies' *marginal* contribution to the system VaR remain widely unchanged (see, e.g., American Express). In most of these cases, the strong increase in VaR is mainly attributed to tail risk spillovers in the network (see also Table 2).

In several cases, increasing individual VaRs coincide with rising systemic risk betas. The most pronounced effect can be observed for Wells Fargo which was not even identified as 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. Other examples include State Street, Progressive Ohio and Marshall & Isley. Here, direct sources for increasing systemic relevance can only be partially found in the network structure (see, e.g., State Street which does not face significant risk spillovers from other companies but a high systemic relevance). For two central nodes in the network, Citigroup and Morgan Stanley, however, declining systemic risk betas overcompensate increasing VaRs resulting in an overall declining systemic relevance. Similarly to AIG, for these firms, network effects play a minor (direct) role.

The above results illustrate that realized systemic risk contributions conveniently condense information on banks' systemic importance. Though, the underlying driving forces of a bank's variation in 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, provides the full picture of companies' specific role in the network and thus builds a solid basis for supervision authorities.

5. Model validation

5.1. A simplistic benchmark

Our measure for systemic relevance requires for each firm a two-step quantile regression with an initial LASSO selection step. Hence, instead of a global comprehensive model for the system VaR, it builds on a collection of tailored partial models which vary for each company to ensure a consistent estimation of individual marginal effects (i.e., systemic risk betas). In this subsection, we illustrate the advantages of our methodology in comparison with a direct one-step estimation of a single global model for the system VaR. In the competing approach, we model the system VaR as a function of all companies' loss exceedances and the set of macroeconomic state variables. [32] Companies are classified as systemically relevant if they are selected as relevant risk drivers for the system VaR. We compare the two techniques along the sets of companies determined as systemically relevant.

In the benchmark case, the system VaR is thus modeled as

$$VaR_{p,t}^{s} = \alpha_1^s + \mathbf{E}_t^{(s)\prime}\boldsymbol{\alpha}_2^s + \mathbf{M}_{t-1}^{(s)}{}'\boldsymbol{\alpha}_3^s, \tag{15}$$

where $\mathbf{E}_t^{(s)}$ and $\mathbf{M}_{t-1}^{(s)}$ are the relevant companies among all 57 possible loss exceedances and the relevant macro-economic indicators, respectively. Positive values of the unkonwn quantile-specific coefficients $(\alpha_1^s, \boldsymbol{\alpha}_2^{s\prime}, \boldsymbol{\alpha}_3^{s\prime})'$ indicate the degree of systemic relevance of each firm. Note that the use of the (standard) LASSO selection mechanism according to Section 3.1 for the benchmark model would result in an unfair comparison as it would only use *one*global penalty for all coefficients and all companies. Conversely, our two-step procedure implicitly assigns firm-specific LASSO penalties. We therefore use an

[32] Note that LASSO selection in a global system VaR model based on all institutions' pre-estimated VaRs would lead to largely imprecise results due to the vast amounts of pre-estimated regressors and inherent multicollinearity effects. We therefore do not include individual (pre-estimated) VaRs but loss exceedances.

adaptive version of the automatic LASSO procedure in (15) which uses regressor-specific weights in the penalty.[33]

Figure 11 summarizes how the group of systemically relevant companies identified by the simplistic benchmark estimation[34] compares to the one determined by our firm-specific two-step approach reported in Table 5. First, there is a considerable overlap of companies which are systemically relevant according to both methods comprising mostly large depositories and insurance companies (group 1). In particular, 17 out of 21 loss exceedances selected by the LASSO in specification (15) also belong to companies whose VaRs also have a systemically relevant effect in our network approach. The four firms which are identified as being relevant only in the benchmark case (group 2) correspond to relatively small companies which appear being "overweighted" by the simplistic approach. The fact that they have been selected may indeed point towards a spurious effect due to co-movements with others. For example, corresponding to our network results, Eaton Vance's (EV) VaR is driven by 12 loss exceedances (see Table 3), but our significance test identifies it as not systemically relevant (see equation (9)). Similar findings hold for ETFC an the two others. The third group of companies comprises those which are not detected as relevant in the simplistic benchmark case, but which showed a significant positive systemic risk beta. Almost all of them are deeply interconnected with other companies, see Table 3. Prominent examples are Morgan Stanley (MS) and Wells Fargo (WFC). In summary, a one-step approach for the system VaR (15) may only serve as a rough tool for a first impression on systemic relevant firms in a moderately interconnected system. As it is, however, not able to capture indirect network effects, it appears to systematically falsely reject systemic relevance of firms gaining their importance mainly

[33]The adaptive LASSO criterion thus minimizes $\frac{1}{T}\sum_{t=1}^{T}\rho_q\left(X_t^s+\alpha_1+\mathbf{E}_t'\boldsymbol{\alpha}_2+\mathbf{M}_{t-1}'\boldsymbol{\alpha}_3\right)+\lambda\frac{\sqrt{q(1-q)}}{T}\sum_{k=1}^{65}w_k\hat{\sigma}_k|\alpha_k|$. The weights w_k are computed as inverses of the absolute values of coefficients from an unrestricted quantile regression, $\hat{\sigma}_k$ is as in (6), λ is determined as in Section A.2., where c is chosen via the in-sample VaR backtest of Berkowitz, Christoffersen, and Pelletier (2011) (see Section A.3.). For details on the adaptive LASSO, see Wu and Liu (2009).

[34]In addition to the selected exceedances, also the change in the short-term interest rate (yield3m) was chosen as a regressor. The detailed results with obtained coefficients are available from the authors upon request.

from their position within the network. Conversely, it tends to falsely attribute systemic relevance to firms with insignificant marginal effects when controlling for the network.

5.2. Case-study: 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 might be less significant 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 distinguish between four broad classes: The first group of highest systemic importance comprises 9 companies with VaRs that significantly influence the system VaR and are among the 25% largest average realized betas. Its most prominent members are AIG, Lehman Brothers, Morgan Stanley, JP Morgan and Goldman Sachs. The second group with "medium" size consists of systemically risky firms with significant systemic impact and average realized betas in the third quartile of the distribution. It mainly contains large depositories and investment banks including Bank of America, Merrill Lynch, Citigroup and Regions Financial, but also the mortage company Freddie Mac. In the third group all companies with small but significant average systemic risk betas are included, in particular those below the median. Finally, the firms which are not detected as systemically risky during the analyzed time period, are collected in the last group.

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 belong 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. See, e.g., the mutual link of Freddie Mac and Fannie Mae, as well as dependencies between Lehman and both Morgan Stanley and Goldman Sachs. Moreover, Merrill Lynch influences Citigroup, and TD Ameritrade Holding as well as E Trade Financial have mutual links to Lehman and Merrill Lynch within the large online broker market. Furthermore, AIG stands out as the by far most interconnected firm in this case study: Its VaR is affected by the tail risks of eight competing insurers and Lehman Brothers while its losses in turn drive VaRs of Citigroup, Aflac, Human, Unum and three other insurance companies.

All four companies of interest have a significant impact on the system. The time evolution of their respective realized betas just prior to the crisis in Figure 10 clearly depicts their increasing systemic riskyness. The exemplary case of Merrill Lynch shows over a longer horizon that the network based idiosyncratic VaR even gradually decreases despite rising systemic importance with a realized risk beta increasing by more than 100% from mid of 2006 to mid of 2007. Moreover, Figure 5 shows that the overall high systemic

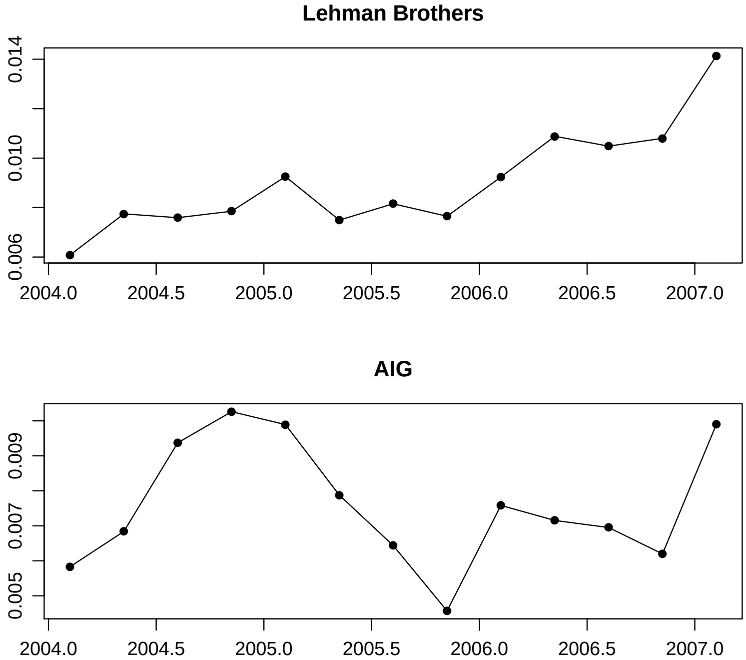

Figure 5: Exemplary time evolution of systemic importance in terms of quarterly realized systemic risk betas from 2004-2007 for the two companies AIG and Lehman Brothers (LEH) belonging to the group of the on average most systemically risky companies. We depict quarterly averages reflecting the quarterly observation frequency of balance sheet characteristics smoothing the exceedance effects in the VaR's.

relevance of Lehmann and AIG can be attributed to very different time evolutions of their realized systemic risk betas well in advance to the crisis. While the systemic relevance of Lehman brothers grows almost monotonically towards the begin of the crisis, the realized beta of AIG already faces a significant high around 2005. It is well documented that from the 1980s on, AIG accumulated vast amounts of complex interconnected positions in credit default swaps (CDS) and other credit securitization derivatives and amounted to the largest holder and issuer of such products. Investigations after the fraud scandal related to the reinsurer Gen Re in 2005 already revealed the large scale systemic impact of the firm. This also induced a rating downgrade and resulted in a reduction of some highly leveraged positions which ultimately build up again towards the crisis. If we compare our results to the findings in Table 4 (page 45 in the Appendix) of Brownlees and Engle (2012), according to their SRISK measure, they also find systemic relevance of LEH, FRE and ML. Though, it is notable that in their 2007 rankings, AIG does not even appear on the top 10 positions, then amounting slowly from mid 2008 to the top five ranks only until January 2009. In this case, our measure incorporates important market information substantially quicker, thus providing a better forward-looking monitoring tool. Likewise, also the high systemic relevance of JPM before the crisis is only picked up by SRISK with a significant time delay.

Our findings clearly show that in June 2007 all four companies were relevant for the stability of the U.S. financial system. They indicate that bailouts during the crisis were justified for Freddie Mac (and the closely tied Fannie Mae) 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.

6. 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 prudent supervisory decisions 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 monitoring tool 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 this would increase 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 $q \in [0,1]$,[35]

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

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)

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

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

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 $\beta^{s|i}_{p,q} = (\beta^{s|i}_{0,p,q}, \boldsymbol{\eta}^{s|i}_{p,q})$. The remaining main part Q in the variance is given by $Q = H'\mathbb{E}[\mathbf{AA}']H$ with $\mathbf{A} = (\mathbf{W}^{(i)}, vec(\mathbf{Z}_{t-1} \cdot$

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

$\mathbf{W}^{(i)\prime}$), $\mathbf{VaR}^{(-i)}$). Denote by $\mathbf{I}$ and $\mathbf{0}$ identity and null matrices, respectively, and by $\mathbf{1}$ a vector of ones of appropriate dimension. Then,

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

where d_Z is the dimension of Z which is 3 in our application, $d_{(-i)}$ is the dimension of $\mathbf{VaR}^{(-i)}_t$, and coefficients $\boldsymbol{\xi}^i_{q,2}$ are those components of $\boldsymbol{\xi}^i_q$ for regressors which appear both in the first and the second step. Correspondingly, $\boldsymbol{\xi}^i_{q,1}$ 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 $\mathbf{VaR}^{(-i)}_t$, 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,

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

Step 2 Repeat step 1 for B=500 times generating the empirical distribution of Λ^i conditional on $\mathbf{W}$ through $\Lambda^i_1, \ldots, \Lambda^i_B$. For a confidence level $\alpha \le 1/K$ 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 $c \le 2$ 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 (6). 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 in Subsection A.3 below.

A.3. Backtest for the model fit for VaR^i

As suggested by Berkowitz, Christoffersen, and Pelletier (2011), for each institution i, we measure VaR exceedances as $I^i_t \equiv I(X^i_t < -VaR^i_{q,t})$. If the chosen model is correct, then,

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

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 Subsection 4.1,

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

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.[36]

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

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

Table 2: Exemplary post-LASSO quantile regressions for VaR^i with $q = 0.05$. Regressors were selected by LASSO as outlined in Section 3.1. Ex.j is the loss exceedance of company j, all other regressors are as in Section 2.2.

	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 i, we list direct risk drivers and risk recipients within the network topology. Respective risk drivers are loss exceedances selected by the LASSO technique (6) as "relevant" regressors for the VaR^i-model ($q = 0.05$) ('Influencing companies'). Direct risk recipients ('Influenced companies') are companies for which the loss exceedance of company i appears as relevant via LASSO in their corresponding VaR^j.

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: Classification of companies with significant and/or time-varying systemic risk betas according to p-values of the respective significance tests. In all cases, the test level is taken as 10% and firms are in alphabetical order within each category. P-values p_{H1} for the test on significance of systemic risk betas in the time period 2000-2008 are depicted in column one (see Hypothesis H1 in Section 4.3). If $\hat{\beta}^{s|i}$ is detected as being significant, then a second test on time-variation of $\hat{\beta}^{s|i}$ in firm-specific characteristics Z_t^i is performed yielding p-values p_{H2} (see Hypothesis H2 in Section 4.3). For firms with a significant but not a time-varying systemic risk beta (lower panel on the left, marked with stars), we re-estimate the systemic risk beta without time-varying interaction terms and test again for its significance. These results (p_{H3}) are included in parentheses in the second column (see Hypothesis H3 in Section 4.3).

Companies with significant $\beta^{s\|i}$		
Name	p_{H1}	p_{H2} (p_{H3})
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
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 $\beta^{s\|i}$	
Name	p_{H1}
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 companies according to **average** realized systemic risk betas over the years 2000-2008 Q3. Most systemic risk contributions are detected as time-varying in systemic risk betas - exceptions with constant $\widehat{\beta}_{av}^{s|i}$ are marked by *. The underlying significance tests are performed as described in Table 4. The third column lists relevant risk drivers for the corresponding firm within the systemic tail risk network. They are determined via the LASSO selection technique (6) as "relevant" loss exceedances to be included in the respective company's VaR^i-regression.

Rank	Name	$\widehat{\beta}_{av}^{s\|i} \cdot 10^2$	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 $\widehat{\overline{\beta}}_t^{s|i}$ at two **specific points in time**. In addition, estimated systemic risk betas and VaRs are listed, illustrating the different sources of variation in $\widehat{\overline{\beta}}_t^{s|i}$. Most systemic risk contributions are detected as being time-varying in systemic risk betas - exceptions with constant $\widehat{\overline{\beta}}_t^{s|i}$ are marked by *. The underlying significance tests are performed as described in Table 4.

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

Rank	Name	$\widehat{\overline{\beta}}_{2007}^{s\|i} \cdot 10^2$	$\hat{\beta}_{2007}^{s\|i}$	$\widehat{VaR}_{2007}^{i}$
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	$\widehat{\overline{\beta}}_{2008}^{s\|i} \cdot 10^2$	$\hat{\beta}_{2008}^{s\|i}$	$\widehat{VaR}_{2008}^{i}$
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 average realized systemic risk betas in the highest quartile: $\hat{\hat{\beta}}_{av}^{s|i} \cdot 100 \in [0.5, 1.3]$. Group 2 refers to the third quartile ('medium') with $\hat{\hat{\beta}}_{av}^{s|i} \cdot 100 \in [0.03, 0.49]$ and Group 3 to realized systemic risk betas lower than the median value ('small'), for which $\hat{\hat{\beta}}_{av}^{s|i} \cdot 100 < 0.01$. 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 as well as betas. Estimation period: January 2000 - June 2007.

Name	influenced by	mainly influencing	overall sign.	average $\hat{\hat{\beta}}_t^{s|i} \cdot 100$	average $\hat{\beta}_t^{s|i}$
FRE	AON, BBT, EV, FITB, FNM, HUM, MBI	BBT, FNM	0.048	0.38	0.092*
ML	AMTD, CB, CNA, HCBK, L, NYB, WRB	C	0.051	0.03	0.030*
LEH	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

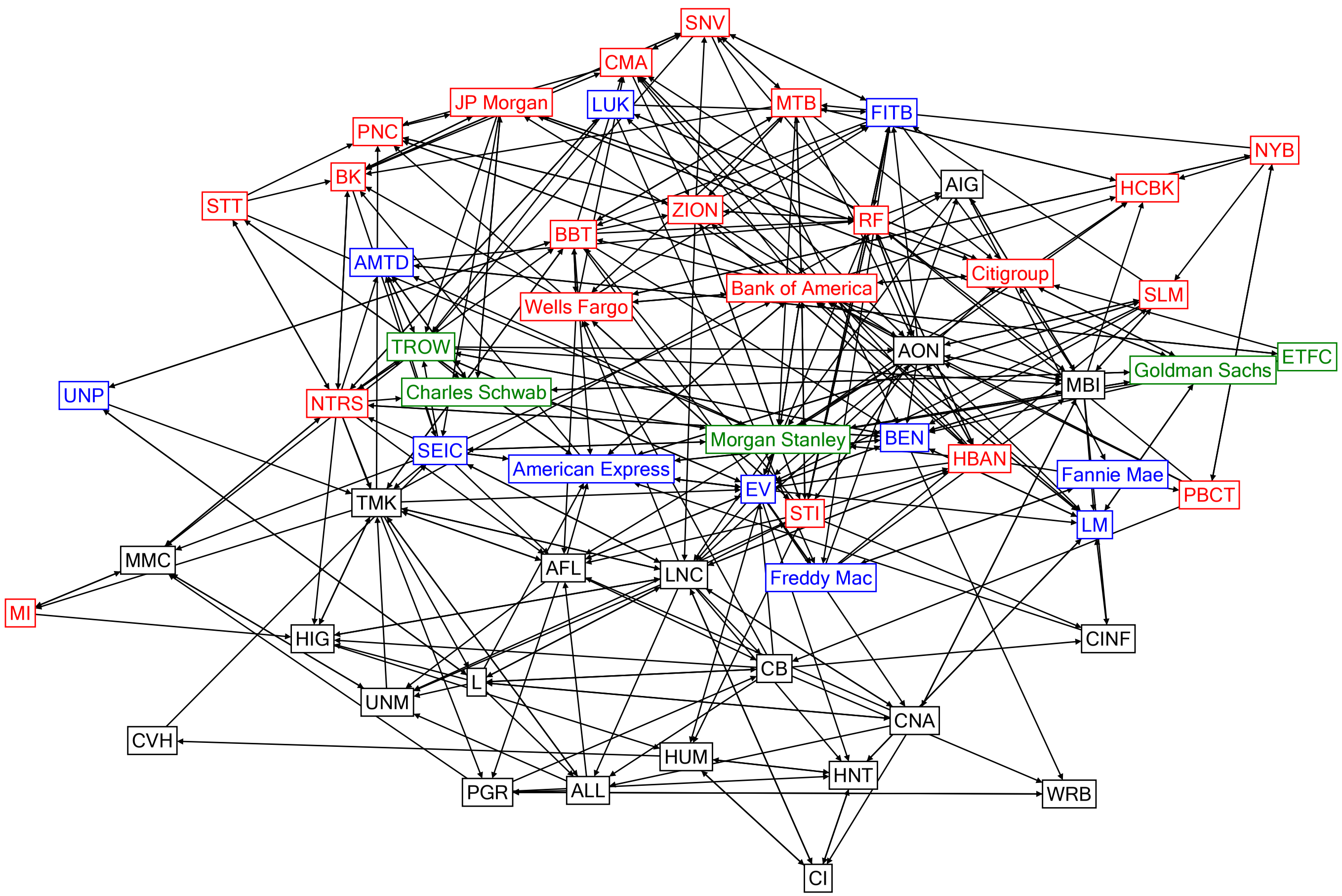

Figure 6: Full network graph for the system of the 57 largest financial companies in the U.S. For simplicity, arrows only mark risk spillovers effects without referring to their respective size. Otherwise arrows and colors are as defined in Figure 1. A complete list of firms' acronyms is contained in Table 1. The graphical allocation is obtained via the Fruchtermann-Reingold algorithm minimizing the total length of all arrows.

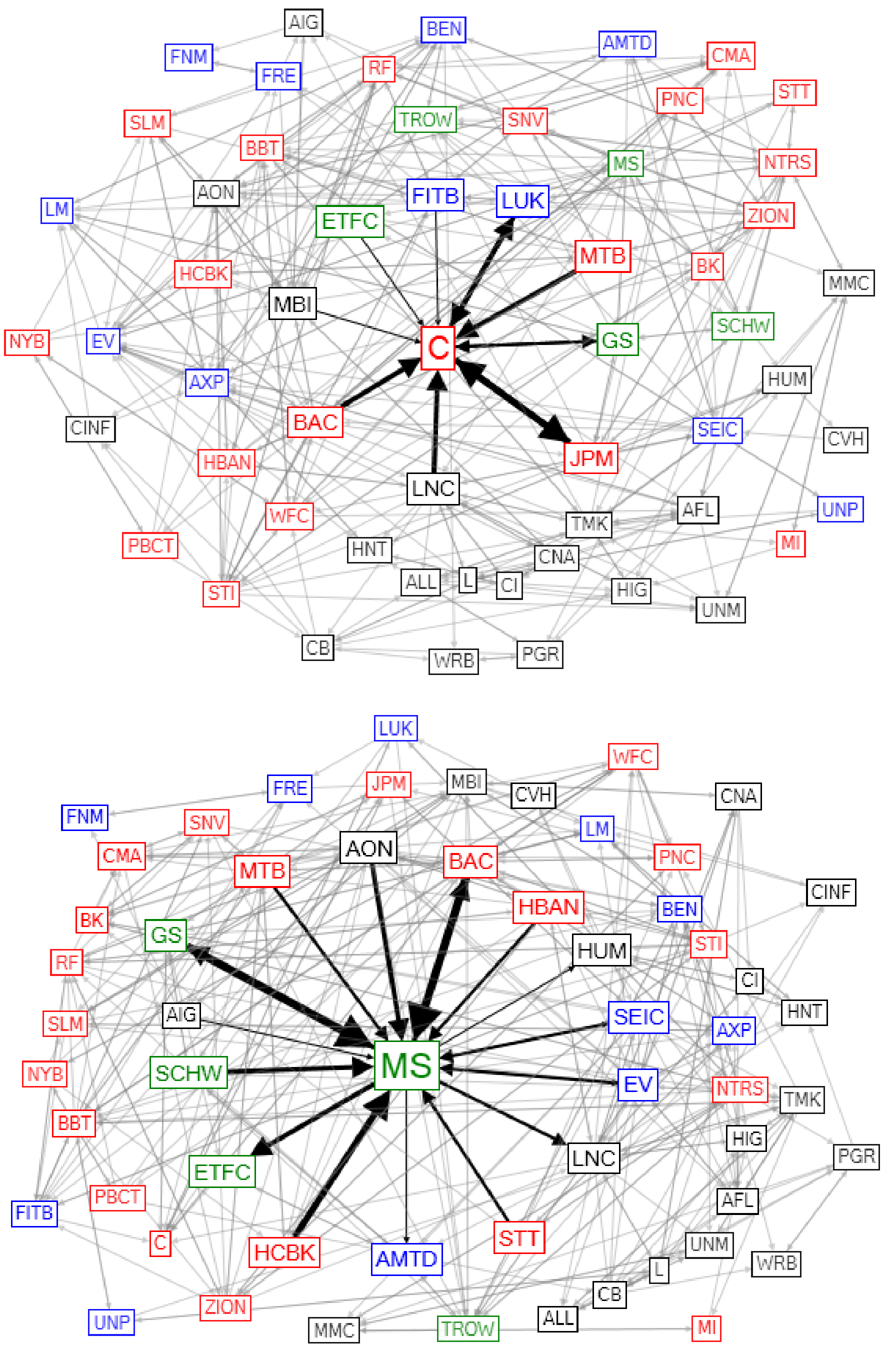

Figure 7: Full Network graphs of Citigroup (C) and Morgan Stanley (MS) highlighting risk drivers and risk recipients directly connected to the respective companies with bold arrows according to the respective size of the effect. Arrows, colors and acronyms are as in Figure 6. For simplicity, all other links just mark spillover effects without referring to size. The list of firm acronyms is contained in Table 1.

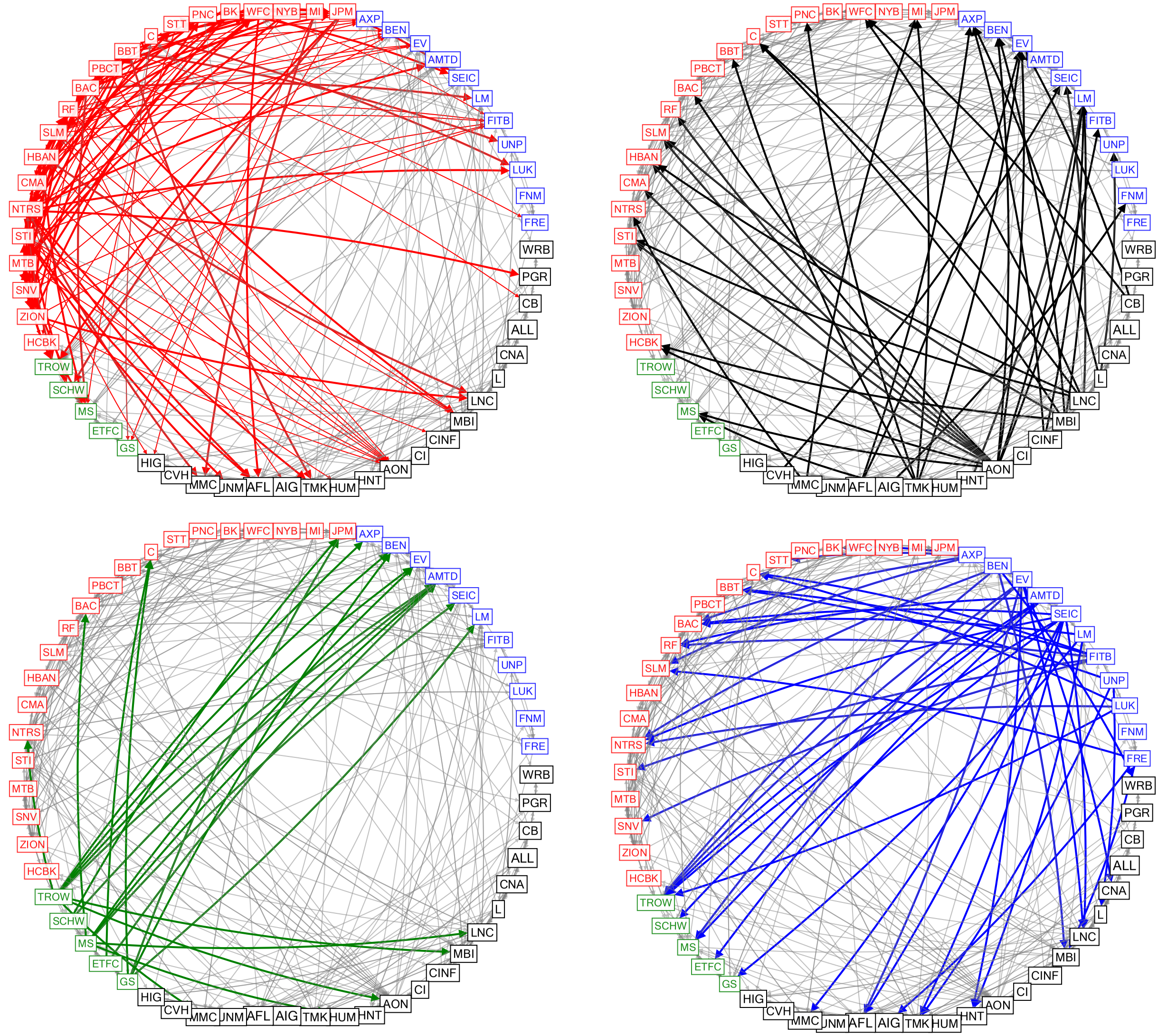

Figure 8: Network graph arranged according to industry groups highlighting the industry-specific risk spillovers from depositories (top left), insurances (top right), broker dealers (bottom left) and others (bottom right). Arrows only mark risk spillovers effects without referring to their respective 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.

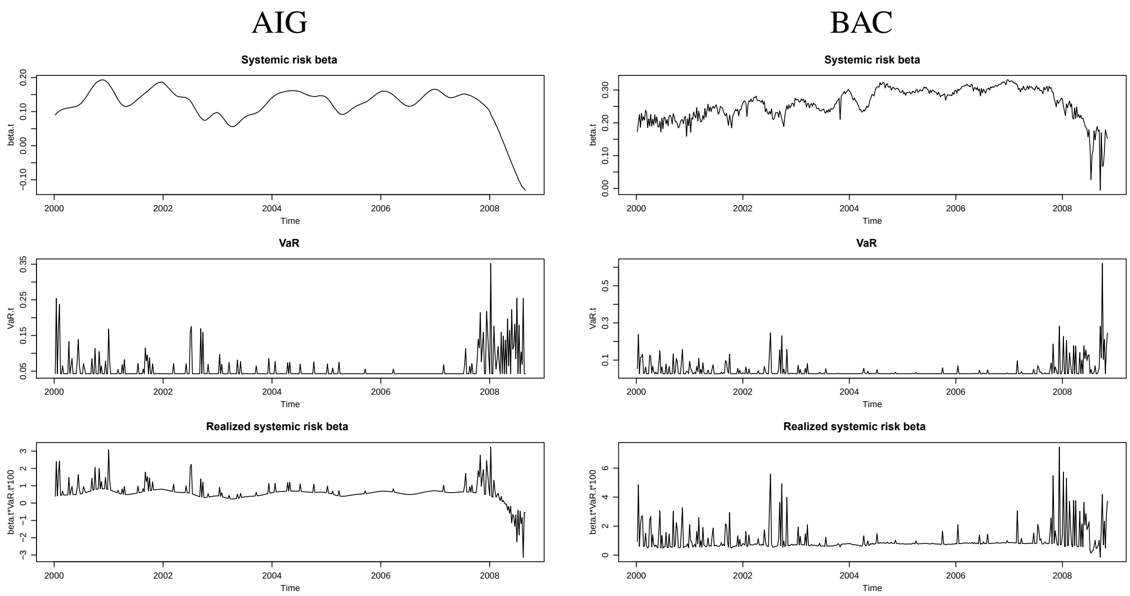

Figure 9: For each of the two institutions, American International Group (AIG) and Bank of America (BAC), the respective column comprises three time series panels which depicts from top to bottom the time-varying systemic risk beta $\widehat{\beta}_t^{s|i}$, the time-varying VaR $\widehat{VaR}_t^{i}$, and the realized systemic risk beta $\widehat{\beta}_t^{s|i}\widehat{VaR}_t^{i}$ of the firm.

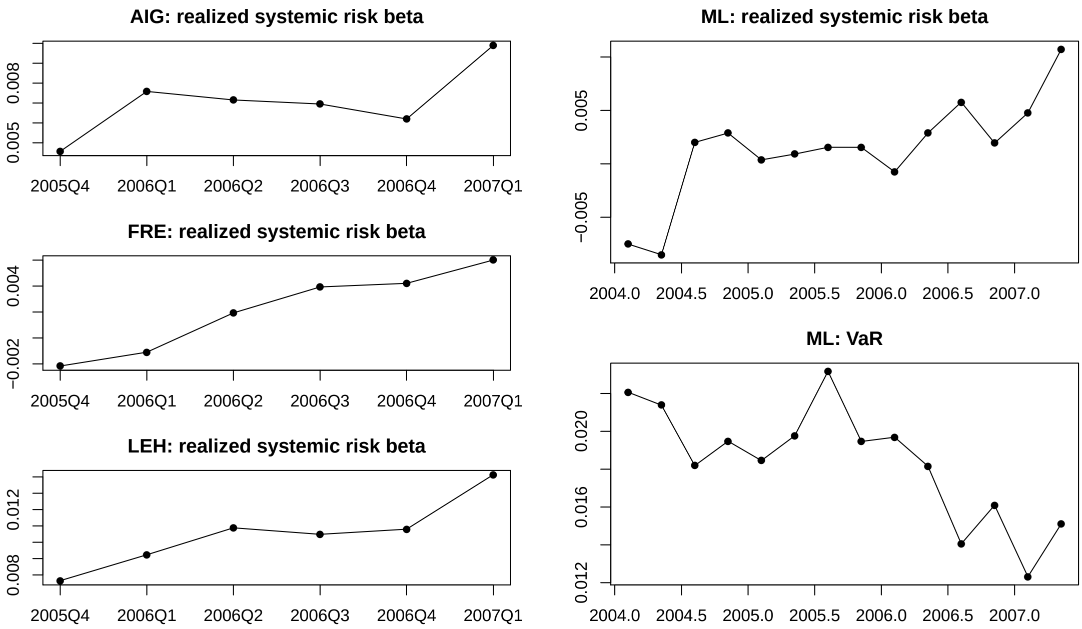

Figure 10: Time evolution of systemic importance for all companies in the focus of the case study. The left column of the panel depicts quarterly averaged realized systemic risk betas of AIG, Freddie Mac (FRE), and Lehman Brothers (LEH) during the period immediately before the crisis. The right column shows quarterly averaged realized systemic risk betas of Merrill Lynch (ML) for the longer time period from 2004 on in comparison to its respective VaR.

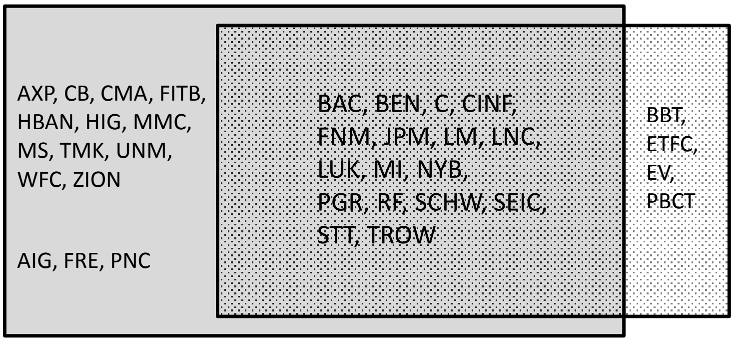

Figure 11: The schematic figure depicts companies classified as being systemically relevant according to our two-step network technique in comparison to a simplistic one-step model with exceedances based on LASSO for (15). Companies in the dotted area are selected by the simplistic model as systemically relevant, firms in the gray area have a significant systemic impact in our network model according to Table 4. Denote the overlay region as group 1 with companies whose tail risks are determined as relevant for the system's risk in both settings. Group 2 are companies in the dotted but non-gray area only selected by the simplistic model. Systemically relevant firms in the gray non-dotted region can be classified as either group 3 being deeply interconnected with other companies with more than 6 links according to Table 3 (upper larger only gray set in the figure) or as group 4 with few, but crucial risk links according to Table 3 (lower only gray set in the figure with three elements).

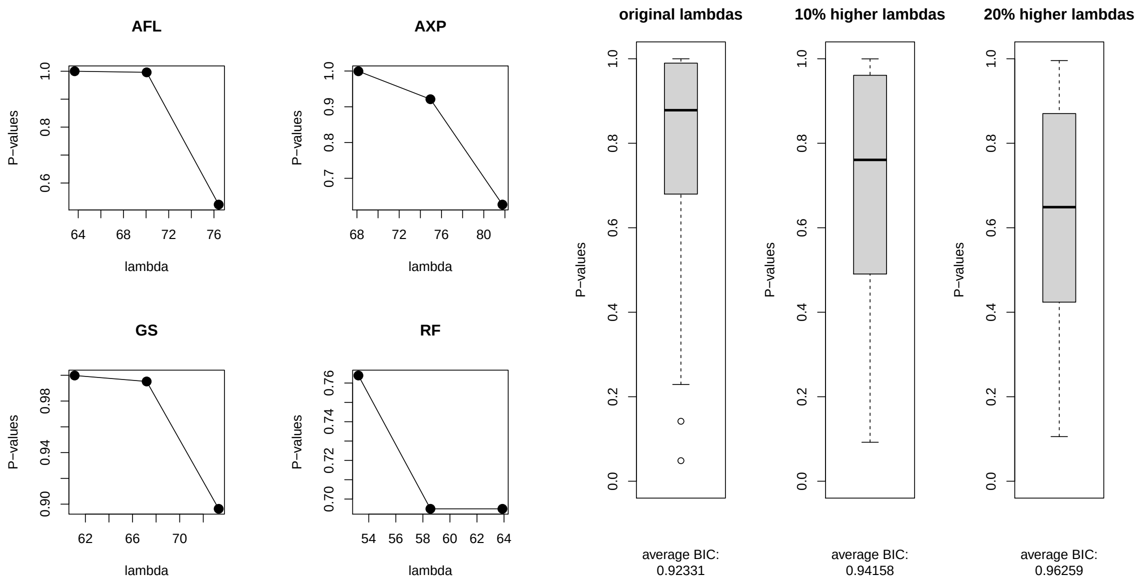

Figure 12: The left panel shows exemplary evolvements of p-values from the VaR^i backtest described in Section 3.3.2 when the individual-specific LASSO penalty parameters λ^i are increased by 10% and 20%. The respective leftmost p-value corresponds to the original choice. The right panel shows boxplots of all p-values obtained from backtesting all the 57 VaR time series. Higher p-values indicate better model fits. At the bottom of the right panel, average values of an additional goodness-of-fit measure, the Bayesian Information Criterion (BIC) for quantiles, are reported. Lower values imply better model fits.

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