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Financial Network Systemic Risk Contributions

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ABSTRACT

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

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

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

The financial crisis 2007-2009 has shown that cross-sectional dependencies between assets and credit exposures can cause even small risks of individual banks to cascade and

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

A general empirical assessment of systemic relevance cannot build on the vast theoretical literature of financial network models and financial contagion, since these results typically require detailed information on intra-bank asset and liability exposures (see, e.g., Allen and Gale, 2000, Freixas, Parigi, and Rochet, 2000, and Leitner, 2005). Such data is generally not publicly disclosed and even regulators can only collect partial information on some sources of inter-bank linkages. Available empirical studies linked to this literature can therefore only partially contribute to a full picture of companies' systemic relevance as they focus on particular parts of specific markets at a particular time under particular financial conditions (see, e.g., Upper and Worms, 2004, and Furfine, 2003, for Germany and the U.S., respectively).[3] Furthermore, assessing risk interconnections on the

[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".

[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).

basis of multivariate failure probability distributions has proven to be statistically complicated without using restrictive assumptions driving the results (see, e.g., Boss, Elsinger, Summer, and Thurner, 2004, or Zhou, 2009, and references therein). Finally, for regulators it is often unclear, how the typically 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, and publicly accessible market as well as balance sheet data. As for risk interconnectedness only dependencies in extreme tails of asset return distributions matter, we base our measure on extreme conditional quantiles of corresponding return distributions quantifying the risk of distress of individual companies and of the entire system respectively. In this sense, our setting builds on the concept of conditional Value-at-Risk (VaR), which is a popular and widely accepted measure for tail risk.[4] For each firm, we identify its so-called *relevant (tail) risk drivers* as the minimal set of macroeconomic fundamentals, firm-specific characteristics and risk spillovers from competitors and other companies driving the company's VaR. Detecting of with whom and how strongly any institution is connected allows to construct a tail risk network of the financial system. A company's contribution to systemic risk is then defined as the induced total effect of an increase in its individual tail risk on the VaR of the entire system, conditional on the firm's position within the financial network as well as overall market conditions. Furthermore, we obtain a reliable measure of a company's idiosyncratic risk in the presence of network spillover effects by assessing its conditional VaR depending on respective tail risk drivers.

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

[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.

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

We determine a company's systemic risk contribution as the marginal effect of its individual VaR on the VaR of the system. In analogy to an (inverted) asset pricing relationship in quantiles we call the measure *systemic risk beta*. It corresponds to the system's marginal risk exposure due to changes in the tail of a firm's loss distribution. For comparing the systemic relevance of companies across the system, however, it is necessary to compute the induced *total* increase in systemic risk. We therefore rank companies according to their "standardized" 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 standardized 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.

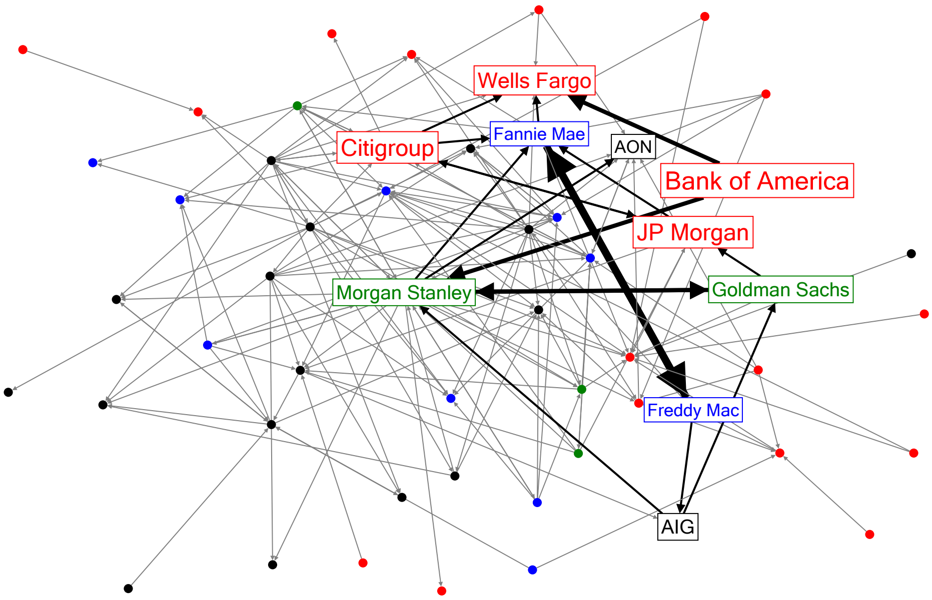

Figure 1: Risk network of the U.S. financial system schematically highlighting key companies in the system with boxes increasing with average size (measured as market valued total assets) in 2000-2008. Details on all other firms in the system only appearing as unlabeled shaded nodes will be provided later in the paper. Depositories are marked in red, broker dealers in green, insurance companies in black, others in blue. An arrow pointing from firm j to firm i reflects an impact of extreme returns of j on the VaR of i (VaR^i) which is identified as being relevant employing statistical selection techniques. 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 arrow where we distinguish between three categories: thin arrows display an increase up to 0.4, medium size of 0.4-0.8, and thick arrows of greater than 0.8. 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.

Our empirical results reveal a high degree of tail risk interconnectedness among U.S. financial institutions. We clearly detect channels of potential risk spillovers which supervision authorities but also risk managers must not ignore. 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 regulatory point of view, the second group of pure risk recipients has the least systemic impact. Monitoring their condition, however, might still convey important accumulated information on potentially hidden problems in those companies which act as their risk drivers. In any

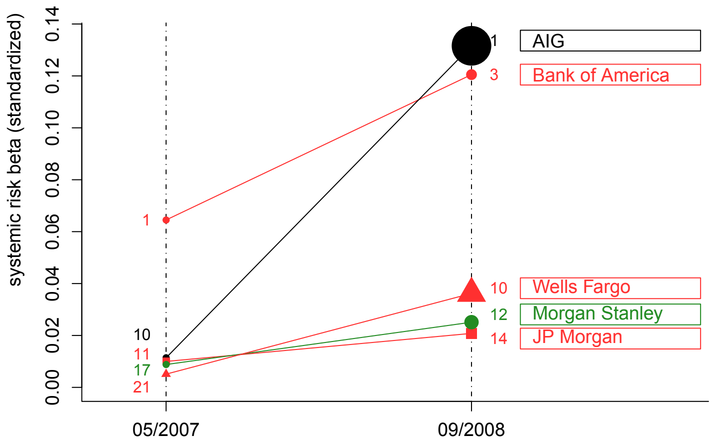

Figure 2: Systemic relevance of five exemplary firms in the U.S. financial system at two time points before and at the height of the financial crisis, 2008. Systemic relevance is measured in "systemic risk betas" quantifying the marginal increase of the VaR of the system given an increase in a bank's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

case, the internal risk management of these companies should account for the possible threat induced by the large degree of dependence on others. In particular, assessing their full risk exposure requires network augmented risk measures as our VaR with preselected network risk drivers. The highest attention of supervision authorities should be attracted by firms which mainly act as risk drivers for others in the system. These contain firms in the center of the network which appear as "too interconnected to fail", but even more so, large depositories at the boundary which drive a small number of firms in the center of the system. 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 (standardized) 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 (standardized) systemic risk betas indicate that most companies' systemic risk contribution sharply increases during the financial crisis. These effects are particularly pronounced for firms, such as, e.g., AIG, which indeed got into financial distress during the crisis and are clearly (ex post) identified as being 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 as 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 AIG, Freddie Mac and Fannie Mae can be justified given their high systemic risk betas and high interconnectedness by the end of 2007.

Our paper relates to several strands of recent empirical literature on systemic risk contributions. Closest to our work is White, Kim, and Manganelli (2010) who propose a bivariate vector-autoregressive system of each company's VaR and the system VaR. They capture time variations in tail risk in a pure time series setting which does not account for mutual dependencies and network effects. In contrast, our model is more structural as it models tail risk in dependence of economic state variables and network spillovers which automatically account for periods of turbulence when predicting the systemic relevance. Similarly, Adrian and Brunnermeier (2010) build on VaR to a construct systemic risk measure without addressing network interconnections and balance sheet characteristics driving individual risk exposures. Moreover, our paper complements papers which measure a company's systemic relevance by focusing on the size of potential bail-out costs, such as Acharya, Pedersen, Philippon, and Richardson (2010) and Brownlees and Engle (2011). Such approaches cannot detect spillover effects driven by the topology of the risk network and might under-estimate the systemic importance of small but very interconnected companies. Moreover, while Brownlees and Engle (2011) study the situation of an individual firm given that the system is under distress, we investigate the reverse relation and measure the effect on the system given an individual firm is in financial trouble. In the same way, we also complement macroeconomic approaches taking a more aggregated view as, e.g., the literature on systemic risk indicators (e.g., Segoviano and Goodhart, 2009, Giesecke and Kim, 2011) or papers on early warning signals (e.g., Schwaab, Koopman, and Lucas, 2011, and Koopman, Lucas, and Schwaab, 2011).

The remainder of the paper is structured as follows. In Section I, we briefly explain the modelling idea and the data. Section II describes the model and estimation procedure for individual companies' VaRs, before presenting results on the financial network structure. Section III discusses the second stage, the system VaR model, including estimation procedure, inference method and empirical results. In Section IV, we robustify and validate our results by presenting a case study of five large financial institutions that were affected by the financial crisis, and try to predict their distress and systemic relevance using only pre-crisis data. Section V concludes.

I. A Framework for Measuring Systemic Relevance

A. Key Concepts

This section provides a compact overview of the major underlying concepts of how we quantify systemic relevance of a company within the financial system network. It introduces major underlying concepts, illustrates how the different steps of the empirical analysis are linked to each other and thus outlines the remainder of the paper. Studying the dependence between systemic risk and firm-specific risk requires modeling relations in the (left) tails of respective asset return distributions, rather than in the center. This is in sharp contrast to a correlation analysis detecting only dependence in mean returns and being inable to quantify spillovers in situations of financial distress.

We consider a stress-test-type scenario for measuring how changes in individual company-specific risk affect the risk of failure of the entire system given the underlying network topology. Therefore, our model does not aim at being structural and building on a general equilibrium framework, but is of reduced form allowing to capture the full *partial* effect for a specific company as its systemic risk contribution. Relevant underlying network linkages between tail risks of firms in the system are identified in a first step and crucially determine each company's tail risk drivers.

We measure systemic risk as the Value at Risk (VaR) of the system return X^s conditional on externalities $\mathbf{B}$.[5] Then, systemic risk at time t is defined as the system's loss position occurring with probability p given externalities $\mathbf{B}$, i.e.,

$$\Pr(-X_t^s \geq VaR_{p,t}^s) = \Pr(X_t^s \leq Q_{p,t}^s) = p \; . \tag{1}$$

Accordingly, $Q_{p,t}^s := Q_p(X^s|\mathbf{B} = \mathbf{B}_t) = Q_p^s(\mathbf{B}_t)$ corresponds to the conditional p-quantile of X^s. The system VaR is defined using the convention that $VaR_{p,t}^s = VaR_p^s(\mathbf{B}_t) = -Q_{p,t}^s$, such that the VaR is non-negative and a higher VaR indicates higher risk as a function of $\mathbf{B}$. The set $\mathbf{B}$ contains macroeconomic variables (as specified below), but also tail risk measures of other financial companies. Obviously, due to strong interconnections, the sum of individual tail risks may substantially differ from overall system tail risk. To quantify the full partial effect of changes in the tail risk of an individual institution on the tail risk of the financial system, we incorporate the tail risk of the specific company in the vector of explanatory variables $\mathbf{B}$ in (1) and quantify its marginal effect on the system VaR.

In this context, we have to overcome several difficulties. First, the tail risk of a company i is not directly observable, but has to be estimated, e.g., by the company-specific conditional Value-at-Risk $VaR_{q,t}^i = VaR_q^i(\mathbf{W}_t)$. For statistical inference, discussed later in the paper, this makes a difference as we have to account for the fact that these variables are pre-estimated leading to nonstandard (increased) confidence intervals. We define $VaR_q^i(\mathbf{W})$ analogously to (1) as $VaR_{q,t}^i = VaR_q^i(\mathbf{W}_t) = -Q_{q,t}^i$, where $Q_{q,t}^i = Q_q^i(\mathbf{W}_t)$ is the conditional q-quantile of company i's return X^i conditional on characteristics $\mathbf{W}$ observed in t. The set $\mathbf{W}_t = (1, \mathbf{M}_{t-1}, \mathbf{E}_t^{-i}, \mathbf{C}_{t-1}^i, X_{t-1}^i)$ contains the the possible *tail risk drivers* of firm i consisting of macroeconomic state variables $\mathbf{M}_{t-1}$, lagged firm-specific characteristics $\mathbf{C}_{t-1}^i$, its lagged return X_{t-1}^i, and loss exceedances of other companies,

[5] The system return is defined as the value-weighted average return of a much larger number of companies than we include in our sample. For details, see Section B.

$\mathbf{E}_t^{-i}$. The loss exceedance of a firm j is defined as $E_t^j = X_t^j 1(X_t^j \leq \hat{Q}_{0.1}^j)$, where $\hat{Q}_{0.1}$ is the 10% sample quantile of firm j's return. Hence, by construction, company j only affects company i if the former is under pressure which naturally captures dependencies between tail risks of companies. Correspondingly, $\mathbf{E}_t^{-i} = (E_t^j)_{j \neq i}$ collects the loss exceedances of all firms apart from company i itself. While firm-specific variables, such as leverage or maturity mismatch can be controlled by the bank itself and can thus be seen as "internal" risk factors, macroeconomic state variables, such as credit spreads or liquidity spreads, and spillovers from other firms under distress are exogenous risk drivers the bank is exposed to.

Define $\mathbf{V}_t = (1, \mathbf{M}_{t-1}, \mathbf{VaR}_q^{-i}(\mathbf{W_t}))$ containing the macroeconomic state variables as well as the VaR levels of all other companies but i in the system. Then, $\mathbf{B}_t$ is the vector $(\mathbf{V}_t, VaR_q^i(\mathbf{W}_t))$ and the so-called *systemic risk beta* is the total marginal effect of firm i's tail risk on the system tail risk,

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

The systemic risk beta can be itself time-varying as it is parameterized in terms of time-varying firm-specific characteristics. This has been suppressed for ease of notation in (2). Systemic risk betas and corresponding rankings comparing the systemic relevance of individual companies are analyzed in Section III.

The second and major difficulty is the question of which risk drivers out of the full sets $\mathbf{V}$ and $\mathbf{W}$ are essential to be included in order to measure $\beta_{p,q}^{s|i}$ unbiasedly while keeping the model parsimonious and thus tractable. Indeed, not all companies are similarly and/or significantly affected by all characteristics and all other firms contained in $\mathbf{V}$ and $\mathbf{W}$. Hence, selecting the statistically *relevant* risk drivers for each company i determines i-specific characteristics $\mathbf{V}^{(i)}$ and $\mathbf{W}^{(i)}$ conditional on which the system VaR is linked to VaR^i. Thus it is sufficient if the reduced form model (2) for $\beta_{p,q}^{s|i}$ only depends on $\mathbf{V}^{(i)}$ and $\mathbf{W}^{(i)}$. Identifying the relevant $\mathbf{V}^{(i)}$ and $\mathbf{W}^{(i)}$, amounts to a model selection problem for the tail risk of firm i which can be solved with an appropriate statistical penalization technique. In particular, we provide a data-driven way to (pre-)select relevant variables $\mathbf{W}^{(i)}$ out of $\mathbf{W}$. Relevant companies appearing in $\mathbf{W}^{(i)}$ are also those which could directly affect $\beta^{s|i}_{p,q}$ in the equation (2) for the system VaR and should thus be contained in $\mathbf{V}^{(i)}$. The model selection step is not only necessary to keep the model parsimonious but also allows to uncover underlying *relevant* tail risk dependencies between companies. Ignoring these spillover effects would lead to a biased measure of systemic risk contribution. Moreover, depicting all relevant risk connections between all firms in the system, results in a network graph for systemic risk which contains valuable regulatory information on potential risk channels and specific roles of companies as risk transmitters and/or recipients. Since the identification of such network effects has to be performed *before* systemic risk betas can be estimated, we present this analysis in Section II before we focus on the estimation of systemic risk betas in Section III.

B. Data

Our analysis focuses on publicly traded U.S. financial institutions. The list of included companies in Table I (see Appendix A) comprises depositories, broker dealers, insurance companies and Others.[6] We use publicly available market and balance sheet data for our assessment of systemic relevance. This is a solid basis for transparent regulation since timely access on detailed information of connections between firms' assets and obligations, is very difficult and expensive to obtain – even for central banks. Daily equity prices are obtained from Datastream and are converted to weekly log returns. To account for the general state of the economy, we use weekly observations of lagged macroeconomic variables $\boldsymbol{M}_{t-1}$ as suggested and used by Adrian and Brunnermeier (2010) (abbreviations as used in the remainder of the paper are given in brackets):

(i) the implied volatility index, VIX, as computed by the Chicago Board Options Exchange (vix),

(ii) a short term "liquidity spread", computed as the difference of 3-month collateral repo rate (available on Bloomberg) and the 3-month Treasury bill rate from the Federal Reserve Bank of New York (repo),

(iii) the change in the 3-month Treasury bill rate (yield3m),

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

(iv) the change in the slope of the yield curve, corresponding to the spread between the 10-year and 3-month Treasury bill rate (term),

(v) the change in the credit spread between BAA rated bonds and the Treasury bill rate (both at 10 year maturity) (credit),

(vi) the weekly equity market return from CRSP (marketret),

(vii) the one-year cumulative real estate sector return, computed as the value-weighted average of real estate companies available in the CRSP data base (housing).

Moreover, to capture characteristics of individual institutions predicting a bank's propensity to become financially distressed, $\boldsymbol{C}_{t-1}^{i}$, we follow Adrian and Brunnermeier (2010) 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) market-to-book value, defined as the ratio of the market value to the book value of total equity (BM),

(iv) size, defined by the logarithm of market valued total assets (SIZE),

(v) equity return volatility, computed from daily equity return data (VOL).

Balance sheets are only available on a quarterly basis and are published on fixed dates (December 31, March 31, June 30 and September 30), while calender weeks start differently every year. As our analysis builds on weekly frequencies, we interpolate the quarterly data to a daily level using cubic splines, and then aggregate them back to the corresponding calendar weeks. As an illustration, Figure 4 shows the interpolated quarterly maturity mismatch times for Wells Fargo. We focus on 57 financial institutions for which data is available during the period from beginning of 2000 to end of 2008, resulting into 467 weekly observations on individual returns, macroeconomic factors and individual characteristics (after interpolation). 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 US financial institutions.

Focusing only on those companies for which a maximum of observations is available yields a higher precision of estimates, however, has the drawback that particularly firms which defaulted during the financial crisis 2007-2009 are excluded from the analysis. Therefore, to validate and robustify our approach, we re-estimate the model over a sub-period ending before the financial crisis and include the investment banks Lehman Brothers and Merrill Lynch that were massively affected by the crisis. This "case study" provides an ex-ante assessment of companies which ex post have been identified as systemically relevant and is given in Section IV.

II. A Systemic Risk Network

A. Network Model and Structure

We assume that the VaR of firm i follows a structural model based on those characteristics $\mathbf{W}^{(i)}$ which are relevant for company i. In particular, in a pre-step, these individual tail risk drivers $\mathbf{W}^{(i)}$ are selected out of lagged macroeconomic state variables, $\mathbf{M}_{t-1}$, returns of other distressed companies in the system, $\mathbf{E}_t^{-i}$, lagged firm-specific characteristics $\mathbf{C}_{t-1}^i$, the i-specific lagged return, X_{t-1}^i, and an intercept. Depicting all connections between all firms and respective companies contained in their set of relevant tail risk drivers produces the corresponding network graph of systemic risk.

A model for VaR^i based on economic state variables as well as loss exceedances by construction automatically adjusts and prevails even in distress scenarios under shocks in externalities. This is a clear advantage compared to pure reduced form time series approaches (cp. e.g. White, Kim, and Manganelli, 2010, and Brownlees and Engle, 2010). For simplicity, we take the underlying model for each VaR_q^i as linear,

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

The coefficients in the model are specific to the considered quantile q underlying the VaR.

In the following, we describe how to statistically select $\mathbf{W}^{(i)}$ for each firm i and provide an appropriate estimation technique for the coefficients $\boldsymbol{\xi}_p^i$. Results for econometric inference are non-standard as consistency and standard errors are affected by the pre-selection step and significance tests in quantile relations require backtesting techniques. We summarize the main results in the text, but provide more technical details in the appendix.

B. Identification of Tail Risk Drivers and Estimation

For each firm i in the system, we jointly observe $(X_t^i, \mathbf{W}_t)$ at all time points $t = 1, \ldots, T$, in the sample with the K-vector of all possible risk drivers $\mathbf{W}_t = (1, \mathbf{M}_{t-1}, \mathbf{X}_t^{-i}, \mathbf{C}_{t-1}^i, X_{t-1}^i)$. According to (1), the firm-specific conditional $VaR_{q,t}^i$ at level q and time point t is defined as the negative conditional q-quantile of X^i given $\mathbf{W}_t^{(i)}$. Thus, at a specific time point $t \in [0, T]$, the structural linear model (3) for the VaR corresponds in the quantile to

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

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

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

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

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

However, the relevant risk drivers $\mathbf{W}^{(i)}$ for firm i are unknown and must be determined from $\mathbf{W}$ in advance. Model selection is not straightforward in the given setting as tests on the individual significance of single variables do not account for the (possibly high) collinearity between the covariates. Moreover, sequences of joint significance test have too many possible variations to be easily checked in case of more than 60 variables. Since alternative model selection techniques, like BIC or AIC, are not available in a quantile setting, we choose the *relevant* covariates in a data-driven way by employing a statistical shrinkage technique known as the least absolute shrinkage and selection operator (LASSO). LASSO methods are standard for high-dimensional conditional mean regression problems (see Tibshirani, 1996), and recently have 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 $\lambda^i \in [0,1]$,

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

with $\mathbf{W}_t = (W_{t,k})_{k=1}^K$, $\hat{\sigma}_k = \frac{1}{T}\sum_{t=1}^{T}(W_{t,k})^2$ and the loss function ρ_q given by (5) (see Belloni and Chernozhukov, 2011). The underlying principle is to select relevant regressors according to the magnitude of their respective coefficients (scaled by the regressor's variation). Regressors are then eliminated if their shrunken coefficients are at (or close to) zero. Here, we eliminate all firms in $\mathbf{W}$ with marginal effects $|\widetilde{\boldsymbol{\xi}}^i|$ being in absolute terms below a threshold $\tau = 0.0001$ and keep only the $K(i)$ relevant regressors $\mathbf{W}^{(i)}$. Hence, LASSO de-selects those regressors contributing only little variation. As all coefficients $\widetilde{\boldsymbol{\xi}}_q^i$ are generally downward biased in finite samples because of the additional penalty term in 7, we then re-estimate the unrestricted model (5) with $\mathbf{W}^{(i)}$ to obtain final estimates $\widehat{\boldsymbol{\xi}}_q^i$. This post-LASSO step produces superior finite sample estimates of coefficients $\boldsymbol{\xi}_q^i$. For more details, see the Appendix.

The selection of relevant risk drivers via LASSO crucially depends on the choice of the company-specific penalty parameter λ^i. The larger λ^i, the more regressors are eliminated. Conversely, in case of $\lambda^i = 0$, we are back in the standard quantile regression setting (5) without any de-selection. Accounting for possible serial dependencies in risk drivers $\mathbf{W}_t$, we determine λ^i in a data-driven way following a bootstrap type procedure as suggested by Belloni and Chernozhukov (2011):

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

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

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 $\alpha \leq 1/K$ in the selection, set

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

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

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

C. Model Validation by Backtesting

We evaluate the adequacy of the VaR estimates by quantifying their in-sample predictive ability. This procedure is an alternative to (infeasible) sequential testing procedures on the joint significance of explanatory variables and, moreover, yields a data-driven way to select c in the LASSO algorithm. In particular, we consider a VaR model as being inadequate if it fails to produce a sequence of independent VaR exceedances over the considered time period. This is formally tested using a likelihood ratio version of the dynamic quantile (DQ) test developed in Engle and Manganelli (2004). Berkowitz, Christoffersen, and

Pelletier (2009) show that the resulting likelihood ratio test has superior size and power properties compared to competing VaR backtesting methods.

For each institution i, we measure VaR exceedances as $I_t^i \equiv I(X_t^i < -VaR_{q,t}^i)$. If the chosen model is correct, then,

$$\mathbb{E}[I_t^i|\Omega_t] = q \; , \tag{8}$$

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 (8) 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

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

we find the asymptotic distribution of the corresponding likelihood ratio test statistic as

$$LR = -2(\ln \mathcal{L}_r - \ln \mathcal{L}_u) \overset{a}{\sim} \chi_5^2 \; . \tag{9}$$

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

The company-specific outcomes of this test are used to choose the parameter c in the LASSO procedure in a data-driven way. In particular, c is chosen such that the p-value associated with (9) for the correspondingly selected model is maximized. This automatically ensures that the LASSO-selected risk drivers for each firm yield optimal in-sample predictions of idiosyncratic tail risk. [7]

D. Idiosyncratic Risks and Systemic Risk Networks: Empirical Findings

D.1. Idiosyncratic Tail Risks

Table II reports the outcomes of the back-testing procedure for the LASSO-selected individual VaR specifications of all 57 financial companies in our sample. We choose q=0.05, i.e., focus on the 95%-quantile of the loss distribution.[8] All selected models provide good in-sample fits with most p-values being well above 0.5. Also the coverages are very close to the nominal level of 5% indicating that the estimated $\widehat{VaR}^i$ series capture company-specific tail risks very well.

For the sake of brevity, we do not report all individual VaR regressions but show exemplary VaR^i (post-)LASSO regressions for companies representing the four branches of depositories, insurances, brokers and others in Tables III and IV. It turns out that the LASSO-selected risk drivers significantly differ across companies. Not surprisingly, this is particularly true for the individually selected loss exceedances of other companies comprising the risk network discussed below. For example, the selected drivers determining the VaR of Goldman Sachs (GS) include, on the one hand, loss exceedances of its biggest competitor, Morgan Stanley (MS) and the insurance company American International Group (AIG). Likewise, Morgan Stanley is driven by the tail risk of many other big companies. Conversely, AIG is influenced by only a few other companies including, however, among others, the mortgage company Freddie Mac (FRE). This risk spillover is highly plausible given the evidence from the financial crisis 2008 and is discussed in more detail

[7] In rare cases, however, the resulting selected model is too small, in the sense that only macroeconomic variables are included. Then, the system VaR regression cannot be performed, because both the individual VaR and the system VaR are linear combinations of the same variables inducing perfect multi-collinearity. In such cases, we decrease the factor c until the most relevant (additional) risk driver is included and the resulting regressor matrix becomes non-singular. In their empirical example, Belloni and Chernozhukov (2011) apply a similar adjustment procedure.

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

below. Note that nearly all loss exceedances have the expected signs: The greater the loss of other companies (i.e., the more negative their returns falling below the 10% quantile), the higher the VaR and thus the potential loss of the firm under consideration. The company-specific accounting variables as well as the macroeconomic state variables enter the regressions mostly with positive coefficients. Particularly, leverage, implied market volatility (represented by the VIX) as well as real estate sector returns positively affect companies' tail risk. The latter reflect firm's sensitivity to rising housing prices which was one of the major causes for the financial crisis in 2008.

Summary statistics of the estimated VaR time series are given in Table V. We observe a substantial variation of VaRs over the cross-section of the sample as well as over time. The reported quantiles of the VaR realizations indicate that company-specific tail risks, i.e., the magnitude of potential losses, strongly vary over time. In fact, for nearly all companies the highest VaRs and thus the highest realizations of idiosyncratic risk are observed during the financial crisis in 2008.

D.2. The Systemic Risk Network

The individually selected loss exceedances of other companies as tail risk drivers for each firm determine the underlying network of risk spillovers. An overview of the identified tail risk connections between all companies is provided in Table VI. We observe that the number of risk connections substantially vary over the cross-section of companies. While some firms such as, e.g., Morgan Stanley, American Express as well as Bank of New York Mellon, are strongly inter-connected and receive substantial tail risk from other companies, there are institutions for which no network effects can be identified at all. These firms are apparently not significantly influenced, but can themselves still act as risk drivers for others.

In order to effectively summarize and to depict the identified risk connections and directions, we graphically present the entire network of companies in Figure 5. Taking all firms as nodes in such a network, there is an influence of firm j on firm i, if E^j is selected 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 $\xi^i_{q,k}$ in $\boldsymbol{\xi}^i_q$ delivers the thickness of the arrow from firm j to firm i in the network graph. If E^j is not selected as relevant risk driver of firm i, there is no arrow from firm j to firm i. Building the network of relevant spillover effects in such a way does not require the relations between companies to be symmetric. This very much corresponds to empirical evidence, as, e.g., Bank of America might strongly influence a small depository, but vice versa there is no direct significant effect. Moreover, note that dependencies between (extreme) quantiles reflect spillovers in *possible* losses (occurring with probability q) but not necessarily in actually realized ones.

We identify four major groups of firms: The first category contains companies with only very few incoming arrows but numerous outgoing ones. These are companies whose potential failure might affect many others but, conversely, which are themselves relatively unaffected by the distress of other firms. We associate these relations with rather "one-sided" network dependencies. Companies belonging to this group are originators of risk spillovers. Hence, their failure can induce substantial risks of failure of the entire system. Therefore, these firms should be particularly monitored by regulatory authorities. These are, e.g., Bank of America (BAC), Citigroup (C), Freddie Mac (FRE), Charles Schwab Corporation (SCHW), MBIA (MBI), Unum Group (UNM) and Hartford Financials (HIG). Bank of America and Citigroup are among the top five largest banks in the U.S. Financial distress of these banks obviously has wide-spread consequences. On the other hand, these banks are sufficiently large and own-standing not to be severely affected by the distress of others. Freddie Mac, one of the two largest U.S. mortgage companies, reveals spillovers particularly to large insurance companies such as AIG and MBIA who hold significant positions in mortgage backed securities. These relationships have been one of the major reasons for the financial crisis 2008. Charles Schwab (SCHW) is one of the largest discount brokers having risk connections to JP Morgan and Morgan Stanley, among others. MBIA, Unum Group and Hartford Financials are large insurance companies. Due to investments in mortgage backed securities, MBIA realized severe losses during the financial crisis. Our network graph reveals a corresponding dependence on Freddie Mac and shows that MBIA itself affects many other firms.

The second group consists of companies which are strongly interconnected with many other firms. These are Morgan Stanley (MS) and JP Morgan (JPM), belonging to the largest banks in the U.S., Fannie Mae (FNM), the main competitor of Freddie Mac, American Express (AXP), one of the biggest financial service companies, as well as the insurance company Lincoln Financial Corporation (LNC). These firms are strongly imbedded in the system and thus are both producers and recipients of tail risk. In several cases, these companies amplify tail risk spillovers by further disseminating risk into new channels. A prominent example is Morgan Stanley which is placed in the center of the network and transports risk in many directions. In particular, Morgan Stanley disseminates spillovers from Bank of America which makes the latter itself deeply interconnected. Due to their role as risk distributors such companies are systemically risky and should be supervised on a regular basis.

The third group contains companies which do not serve as major risk producers but are themselves potentially affected by many other institutions. An interesting example is the Bank of New York Mellon (BK) revealing substantial risk input. This is illustrated in Figure 3 depicting the specific role of Bank of New York in the systemic risk network. The bank receives risk spillover from many other institutions including several large depositories and broker dealers. This is due to the fact that it serves as one of the major clearing banks in the U.S. Accordingly, its risk increases as soon as its large corporate customers become financially distressed. Further examples are Allstate Corporation (ALL), the second-largest personal lines insurer in the U.S., and Cincinnati Financial Corporation (CINF), a company for property and causalty insurance. Finally, we identify a group of companies revealing strong risk connections with only very few other firms. Examples of these predominantly bilateral dependencies are connections between Morgan Stanley and Citigroup, Freddie Mac and Fannie Mae as well as between Goldman Sachs and JP Morgan.

Distinguishing between these four industry groups, we observe that depositories tend to be less involved than insurance companies. Most insurances are placed in the center of the network graph and thus serve as both risk recipients and transmitters. The same is true for broker dealers which tend to be even stronger interconnected. As discussed

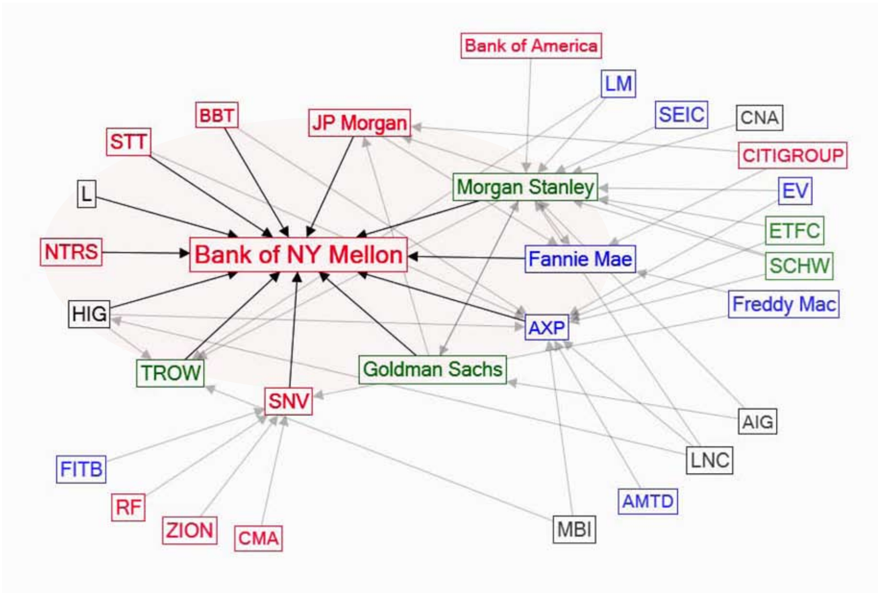

Figure 3: Schematic subgraph of the risk network of the U.S. financial system highlighting the role of the Bank of New York Mellon (BK) in bold as a major clearing house. For simplicity, arrows only mark risk spillovers effects without referring to their respective size, otherwise they are as defined in Figure 1. Likewise, the colors are defined as in Figure 1. Arrows are only displayed in this figure if pointing towards BK. The graph only contains firms with a direct influence on BK (in the shaded ellipsoid closest to BK) and those which might influence BK on a "second level" (in the larger ellipsoid). A list of their abbreviations is contained in Table I.

above, an extreme example is Morgan Stanley which is heavily involved and imports as well as exports tail risk in many directions. In contrast, several depositories are placed at the edge of the network and tend to serve rather as risk transmitters than recipients. Typical examples are Bank of America and Citigroup which are, however, themselves strongly connected to risk distributors which further disseminate tail risk.

Figure 6 shows a subset of the network depicting only the risk linkages of Citigroup. The number of possibly affected banks might be used as an indicator of Citigroup's systemic relevance. Holding fixed Citigroup's tail risk inflow (from LNC and JPM), this ”network tree” graphically presents how financial distress is transmitted through the system. Figure 7 presents the corresponding network tree for Morgan Stanley. As discussed above, this company shows bi-directional risk connections with numerous other companies. Therefore, in this case, causal interpretations are harder and require to condition on the risk in-flows of several other firms. However, the topology of this sub-network looks quite different than that of Citigroup. The latter has only a few direct connections with other firms which are, however, further distributed in many other directions in the next layers. Conversely, Morgan Stanley has more neighbors which are directly affected by risk spillovers which are still further multiplied in the second level.

Hence, though a risk network does not allow to quantitatively assess the systemic relevance of a financial institution, the degree of firms' interconnectedness and the specific topology of the network or corresponding sub-networks allows to identify possible risk channels in the system. These interlinkages are central for macroprudential regulation. They reflect the particular role of a firm as risk recipient, transmitter or distributor of tail risk. In this sense, systemic risk networks provide valuable accompanying information for a reduced-form analysis quantifying the marginal effects of individual distress on the system. Such an analysis is performed in the following section.

III. Quantifying Systemic Risk Contributions

A. A Reduced Form Model for Systemic Risk Betas

Our main focus is to provide an accurate but parsimonious measure of 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. For an unbiased marginal effect, however, it is sufficient just to control for all firm i-specific risk drivers in a corresponding reduced-form model. Conversely, a fully-fledged structural general equilibrium model is not necessary and, even if correctly specified, would be almost impossible to estimate, given the high-dimensionality and interconnectedness of the financial system on the one hand and data availability on the other. Moreover, variables unrelated to VaR^i do not affect firm i's systemic risk contribution.[9] For this reason, we propose estimating systemic risk contributions based on reduced-form models which are specific for each firm i as they only

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

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

$$VaR^s_{p,t} = \mathbf{V}^{(i)\prime}_t \boldsymbol{\gamma}^s_p + \beta^{s|i}_{p,q} VaR^i_{q,t}, \tag{10}$$

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

The systemic risk beta $\beta^{s|i}_{p,q} = \beta^{s|i}$ of company i captures the effect of a marginal change in VaR^i_t on VaR^s_t. It can be interpreted in analogy to an inverse asset pricing relationship in quantiles, where bank i's return quantiles drive the quantiles of the system given network-specific effects and firm-specific and macroeconomic state variables. Accordingly,

$$\bar{\beta}^{s|i}_{p,q} := \beta^{s|i}_{p,q} VaR^i_t \tag{11}$$

measures the full partial effect of a tail risk increase of bank i on VaR^s_t. We refer to $\bar{\beta}^{s|i}_{p,q}$ as *standardized* systemic risk beta since it allows to cross-sectionally compare systemic risk contributions and to rank banks according to their systemic relevance.

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

$$\beta^{s|i}_{p,q,t} = \beta^{s|i}_{0,p,q} + \mathbf{Z}^{i}_{t-1}{}' \boldsymbol{\eta}^{s|i}_{p,q}, \tag{12}$$

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

We suggest choosing Z_t^i as a subset of C_t^i consisting of the major drivers of a bank's distress such as size, leverage, and maturity mismatch. As a testable hypothesis, we postulate that these variables do not only affect a bank's VaR, but simultaneously also drive its marginal systemic relevance. As a consequence, rankings based on $\beta_t^{s|i}$ directly control for size, leverage, and maturity mismatch and do not require any ex-post adjustments for these characteristics. Due to the linearity of (12) we can thus write the quantile model (10) for VaR_p^s with time-varying $\beta_{p,q,t}^{s|i}$ in the following form

$$VaR_{p,t}^s = \mathbf{V}_t^{(i)\prime}\boldsymbol{\gamma}_p^s + \beta_{0,p,q}^{s|i} VaR_{q,t}^i + (VaR_{q,t}^i \cdot \mathbf{Z}_{t-1}^i)' \boldsymbol{\eta}_{p,q}^{s|i} \,. \tag{13}$$

B. Estimation and Inference

If firm specific VaRs were directly observable, the magnitude and significance of i-specific systemic risk betas could be directly inferred from the linear quantile regression (13) with the VaR defined by (1). However, note that the regressors VaR_t^i and $\mathbf{VaR}_{q,t}^{(-i)}$ in $\mathbf{V}^{(i)}$ are pre-estimated as they arise from the first-step quantile regressions as shown in Section II. Hence, operationalizing (13) with $\widehat{VaR}_t^i$ and $\widehat{\mathbf{VaR}}_{q,t}^{(-i)}$ as generated regressors, yields the (second step) quantile regression,

$$\begin{aligned} X_t^s &= -\widehat{\mathbf{V}^{(i)}}_t^{\prime}\boldsymbol{\gamma}_p^s - \beta_{0,p,q}^{s|i} \widehat{VaR}_{q,t}^i - (\widehat{VaR}_{q,t}^i \cdot \mathbf{Z}_{t-1}^i)' \boldsymbol{\eta}_{p,q}^{s|i} + \varepsilon_t^s, \\ &\text{with} \quad Q_p(\varepsilon_t^s | \widehat{VaR}_{q,t}^i, \widehat{\mathbf{V}}_t, \mathbf{Z}_{t-1}^i) = 0 \,. \end{aligned} \tag{14}$$

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

$$\frac{1}{T}\sum_{t=1}^{T} \rho_p \left(X_t^s + \widehat{\mathbf{V}^{(i)}}_t^{\prime}\boldsymbol{\gamma}_p^s + \beta_{0,p,q}^{s|i} \widehat{VaR}_{q,t}^i + (\widehat{VaR}_{q,t}^i \cdot \mathbf{Z}_{t-1}^i)' \boldsymbol{\eta}_{p,q}^{s|i} \right) \tag{15}$$

in the unknown parameters. Consequently, the resulting estimate of the full time-varying marginal effect $\widehat{\beta}^{s|i}_{p,q}$ in (12) is obtained as

$$\widehat{\beta}^{s|i}_{p,q,t} = \widehat{\beta}^{s|i}_{0,p,q} + \mathbf{Z}^{i}_{t-1}{}' \widehat{\boldsymbol{\eta}_{p,q}}^{s|i} \tag{16}$$

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

Since $VaR^{i}_{q,t}$ is a function of $\mathbf{W}^{(i)}$, conditional quantile independence in (14) is equivalent to $Q_p(\varepsilon^s_t|\mathbf{W}^{(i)}_t, \mathbf{W}^{(-i)}_t, \mathbf{Z}^{i}_{t-1}) = 0$ where $\mathbf{W}^{(-i)}_t$ stacks $\mathbf{W}^{(j)}_t$ for all firms relevant for company i appearing in $\widehat{\mathbf{VaR}}^{(-i)}_{q,t}$. Hence, with both quantile regression steps being linear, inserting (3) into (13) yields a full model for the system's tail risk in observable characteristics. However, direct one-step estimation is only feasible if the choice of $W^{(i)}$ and thus $\mathbf{VaR}^{(-i)}_{q,t}$ is still determined in a pre-step from individual VaR regressions. Model selection based on the full model of VaR^s in observables is infeasible since correlation effects among the huge number of regressors would produce unreliable results. Furthermore, individual parameters $\beta^{s|i}_{0,p,q}$ and $\boldsymbol{\eta}^{s|i}_{p,q}$ could not be identified without additional identification condition $Q_q(\varepsilon^i_t|\mathbf{W}^{(i)}_t) = 0$, implicitly bringing back the first-step estimation. Therefore we use two-step estimation even if exact asymptotic confidence intervals are larger than for an (infeasible) single step procedure. In contrast to mean regressions, such results are non-standard in a quantile setting and are therefore provided in detail in the Appendix. In finite samples, however, asymptotic distributions often only provide a poor approximation to the true distribution of the (scaled) difference between the estimator and the true value if sample sizes are not sufficiently large. In case of quantile regressions, this effect is even more pronounced, since valid estimates for the asymptotic variance follow poor non-parametric rates and thus require even larger sample sizes to obtain the same precision.

Therefore, for judging the quality of the estimates $\hat{\beta}^{s|i}_{p,q,t}$, we suggest a procedure for testing their significance which is valid in finite samples. In the given setting, we aim at testing for the significance of a systemic risk beta, and/or time-variations thereof. We adapt a test proposed by Chen, Ying, Zhang, and Zhao (2008) for median regressions to a quantile setting. The test statistic is

$$S_T = \min_{\boldsymbol{\xi}^s \in \Omega_0} \sum_{t=1}^{T} \rho_p(X_t^s - \mathbf{B}_t' \boldsymbol{\xi}^s) - \min_{\boldsymbol{\xi}^s \in \mathbb{R}^{d_B}} \sum_{t=1}^{T} \rho_p(X_t^s - \mathbf{B}_t' \boldsymbol{\xi}^s), \tag{17}$$

with the compound vector of all regressors in VaR^s, $\mathbf{B}_t \equiv (VaR_t^i, VaR_t^i \cdot \mathbf{Z}_{t-1}^i, \mathbf{V}_t^{(i)})$, corresponding parameter d_B-vector $\boldsymbol{\xi}^s$, and Ω_0 refering to the constrained set of parameters under H_0. The asymptotic distribution of S_T 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

$$\begin{aligned} S_T^* \quad = \quad & \min_{\boldsymbol{\xi}^s \in \Omega_0} \sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t' \boldsymbol{\xi}^s) - \min_{\boldsymbol{\xi}^s \in \mathbb{R}^{d_B}} \sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t' \boldsymbol{\xi}^s) \\ & - \left(\sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t' \hat{\boldsymbol{\xi}}_c^s) - \sum_{t=1}^{T} w_t \rho_p(X_t^s - \mathbf{B}_t' \hat{\boldsymbol{\xi}}^s) \right), \end{aligned} \tag{18}$$

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.[10]

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

C. Empirical Evidence on Systemic Risk Betas

We estimate systemic risk betas according to (14) with their time variation driven by $\mathbf{Z}^i$ consisting of a firm's leverage, maturity mismatch and size. Hence, time-variations of systemic risk betas are exclusively due to changes of firm-specific effects. As a consequence, systemic risk contributions of two companies with the same exposure to macroeconomic risk factors and financial network spillovers may be still different as they depend on their balance sheet structures. 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 supress the quantile index as we set $p = q$.

Table VII reports the point estimates for $\beta_0^{s|i}$, the constant (marginal) effect of VaR^i on VaR^s as well as the parameters associated with the interaction variables, $\eta_{MMM}^{s|i}$, $\eta_{SIZE}^{s|i}$ and $\eta_{LEV}^{s|i}$. Note that a positive systemic risk beta indicates that an increase in $\widehat{VaR}^i$ (expressed as a positive number) induces an increase of the conditional quantile of the negative system return distribution and thus rises the risk of distress of the system.

In order to test whether a company's systemic relevance is statistically significant, we test its systemic risk beta against zero, i.e., $\beta_t^{s|i} = 0$. This test requires testing for the joint significance of all variables driving a firm's marginal impact leading to the hypothesis

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

If this null hypothesis cannot be rejected, an increase of the company's possible loss position, given all economic state variables and i-specific risk inflows from other companies, does not induce a significantly higher potential systemic loss. Accordingly, we consider such a company as not being systemically relevant. To test whether systemic risk betas are time-varying, we test the joint hypothesis

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

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

The underlying tests are performed using the wild bootstrap procedure illustrated in Section B based on $2,000$ resamples of the test statistic. The results are reported in form of p-values in Table VII. According to our test outcomes we distinguish between three groups of companies. In the upper part of the table, we report the estimates of systemically relevant companies with time-varying systemic risk betas (i.e., rejecting both hypotheses **H1** and **H2**), while in the middle panel, we show results for firms that are systemically relevant but reveal time-invariant betas (i.e., rejecting **H1** but not **H2**). Finally, the lower panel contains institutions that are not significantly systemically relevant. The underlying significance level is chosen to be 10% as the number of observations is not very large relative to the number of regressors, in particular, when considering the two-stage regression setting.

As shown by Table VII, various companies are systemically not relevant as their marginal contributions to the system's tail risk are not significant. Confirming the network analysis in Section D.2, most of these companies do not serve as tail risk drivers for other firms. Notable exceptions are the two government-sponsored companies (GSEs) Federal National Mortgage Association (Fannie Mae) and Federal Home Loan Mortgage Corporation (Freddie Mac). The latter were massively affected by the financial crisis and were bailed out by Federal Reserve and U.S. Treasury in July 2008. The fact that these companies are not significantly systemically relevant through the entire sample period is obviously due to a structural change in September 2008, when the two GSEs were placed under conservatorship of the U.S. government. To provide deeper insights into such effects, we re-visit the systemic importance of Fannie Mae and Freddie Mac, among others, by explicitly focusing on a period *before* the crisis in Section IV. Moreover, more than half of all insurance companies are shown to be systemically not relevant. As pointed out by Schich (2009), many of these companies were also not too much affected during the financial crisis 2007-2009 as their investment portfolios mainly contained stocks and bonds rather than mortgage-backed securities.

Overall, the majority of systemically relevant companies are banks. Among the (significantly) systemically relevant firms, several companies reveal systemic risk betas for which we cannot identify significant time variations in dependence of company-specific characteristics. Hence, those companies' marginal contributions to systemic risk are obviously not affected by their size, leverage, and maturity mismatch. Examples are Regions Financial, Zions Corporation and JP Morgan with comparably high systemic risk betas across time and the cross-section of institutions. In contrast, for many other firms, we indeed find significant time-varying marginal effects on systemic risk. As reported by Table VII, the coefficients associated with maturity mismatch, size and leverage driving the time variation in systemic risk betas are dominantly positive. Thus marginal systemic relevance increases if a company becomes larger and is exposed to higher idiosyncratic risk.[11]

Important examples of companies with highly significant and time-varying systemic risk betas are Bank of America and AIG. AIG was among the largest issuers and holders of credit default swaps (CDS) and other credit securitization derivatives before the crisis. Its obviously strong exposure to mortgage default risks is reflected by a strong dependence to Freddie Mac as reflected in the network graph in Figure 5. Consequently, AIG faced tremendous write-downs in 2008, and received rescue packages amounting to USD 150 billion (see Schich, 2009). Our finding of AIG being systemically relevant quantitatively complements our results on AIG's network dependencies (see Section D.2) revealing *how* AIG's tail risk affects the financial system. In fact, AIG produces risk spill-overs to Goldman Sachs and Morgan Stanley, among others. As discussed above, particularly Morgan Stanley is deeply interconnected and serves as multiplier of tail risk. Its strong link to AIG is obviously a major channel for the formation of systemic risk. The upper part of Figure 8 depicts the AIG-specific estimates of $\beta_t^{s|i}$ and VaR_t^i as well as the product thereof, $\bar{\beta}_t^{s|i}$, measuring the standardized systemic risk contribution. We observe that systemic risk betas significantly vary over time and particularly increase during the financial crisis. Likewise, the firm's VaR strongly increases during the crisis period reflecting also severe idiosyncratic risk. Naturally the same pattern is revealed by the standardized systemic risk beta $\bar{\beta}_t^{s|i}$. Though on first sight, it seems to be counter-intuitive that towards the end of the sample, both $\hat{\beta}_t^{s|i}$ and $\widehat{\bar{\beta}}_t^{s|i}$ decrease, this pattern is explained by the fact that

[11] However, because of multi-collinearity between these variables, the interpretation of individual coefficients is rather difficult. Therefore, it is more reasonable to analyze their total impact on systemic risk betas resulting in variations over time. This analysis is performed in Section D.

the rescue packages from the Federal Reserve were issued in September 2008. This step signficantly reduced the risk of both AIG's and the entire system's failure.

Another example is Bank of America. As discussed in Section D.2, Bank of America serves as a tail risk driver for others but is not a tail risk recipient. Our estimates indicate that its risk channels, particularly to Morgan Stanley, are systemically critical. Figure 8 shows that Bank of America's systemic risk beta has been relatively stable before the financial crisis but significantly dropped after the issuance of the Federal Reserve's rescue packages. Nevertheless, its VaR and thus its standardized systemic risk beta strongly increased during the crisis and particularly thereafter. The average standardized systemic risk beta computed over the entire sample period indicates that a 1% increase of the VaR induces a 8.7 basis point increase of the system VaR.

To cross-validate our findings with external evaluations of banks' systemic importance we refer to the Supervisory Capital Assessment Program (SCAP) conducted by the Federal Reserve in spring 2009. The 19 largest bank holding companies went through comprehensive investigations resulting in estimates of a potential lack of capital buffer to cover their risks under an adverse macro scenario. In this analysis, detailed information on balance sheet positions were used, including data which are not publicly available. For details, see Federal Reserve System (2009). Since the SCAP took place right after the end of our sample period, it is insightful to compare the outcomes with our results and to check whether our model, which uses more aggregated data, is still able to detect the systemic riskiness of those companies that, according to the SCAP, faced capital shortage in the stress test scenario. Indeed, the financial institution with the biggest potential lack of capital buffer according to the SCAP, Bank of America, is among our systemically relevant companies, with a highly significant systemic risk beta $\beta_t^{s|i}$. In addition, with Citigroup, FifthThird Bancorp, Morgan Stanley, PNC, Regions Financial, SunTrust Banks and Wells Fargo we identify all eight banks contained in our database[12] which, according to the SCAP results, were threatened by financial distress under more adverse market conditions. This becomes even more evident in light of the systemic risk rankings as shown in Section D.

[12]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.

In summary, we find that the estimates of systemic risk betas seem to reflect companies' systemic riskiness very well. Our results are strongly in line with the actual situations the included financial institutions were facing during the sample period. Moreover, our findings confirm the empirical evidence and developments observed during the financial crisis in 2008. For a further robustification of our results, we separately study only the pre-crisis period in Section IV.

D. Rankings of Systemic Risk Contributions

Systemic risk contributions of firms measured by respective systemic risk betas (11) might be time-varying. Their standardized form can be used to obtain rankings of companies' systemic relevance at any point in time.

We use the outcome of the statistical tests from the previous subsection to decide whether a systemic risk beta should be treated as being time-varying or time-invariant. In particular, we keep the most general time-varying model whenever time-invariance of systemic risk betas can be rejected at the 10%-level. In this case, the standardized systemic risk beta $\bar{\beta}_t^{s|i}$ varies over time through two channels: a time-varying beta, $\beta_t^{s|i}$ and a time-varying Value-at-Risk, VaR_t^i. Conversely, for companies with constant systemic risk betas (middle panel of Table VII), the observed time variation in standardized systemic risk beta (11) originates only from time variations in VaR^i. In this case, we re-estimate the model with constant systemic risk betas with the corresponding estimation results given in Table VIII. As an additional backtest, we also provide results for the significance of such constant betas, i.e., we test the hypothesis

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

In all but one case, **H3** is rejected on a 10% significance level.[13] Moreover, note that conclusions on a company's systemic relevance are only sensible if the systemic risk impact $\beta^{s|i}$ is positive, implying that an increase in VaR^i also increases the system VaR.

[13]The only exception is the insurance company Torchmark, where the p-value is 0.36. Consequently, we ultimately exclude it from the category of systemically relevant companies.

As reported by Tables VII and VIII, this is not the case for very few companies which we exclude from the ranking analysis. Consequently, not all companies necessarily appear in all rankings in Tables IX to XI.

To provide an overview, Table IX gives a ranking based on averaged standardized systemic risk betas over the period from 2000 to 2008. Accordingly, Bank of America is identified as being systemically most risky with a (standardized) systemic risk beta being more than double than that of the next largest ones. However, note that *average* systemic risk betas only provide an incomplete picture as they aggregate companies' marginal systemic risk contributions and VaRs over time ignoring potential changes in the structure of the financial sector. Accordingly, apart from Bank of America, most companies reveal relatively similar average risk contributions over the considered period. Therefore, in this context, differences in ranks between companies should not be overinterpreted.

In contrast, monitoring the evolution of systemic risk betas over time provides a more informative picture on companies' specific systemic importance and yields valuable feedback from the market for forward-looking regulation. To illustrate the potential of our approach, we show the rankings at two specific time points: Table X gives the systemic risk ranking for the last week in May 2007, which was a relatively "calm" time before the start of the financial crisis. Table XI, on the other hand, shows the ranking at the end of September 2008, shortly after the collapse of Lehman Brothers. Comparing the pre-crisis and post-crisis rankings, we observe clear changes. Overall, systemic risk betas – and thus the magnitude of systemic risk contributions – have sharply increased. The strongest effects are identified for Fifth Third Bancorporation showing the lowest standardized systemic risk beta in 2007 (among the group of systemically relevant firms) and belonging to the most risky companies in 2008. This evolution is reflected by a 50-fold increase of the standardized systemic risk beta. Likewise, we observe a 12-fold increase for AIG, a 10-fold increase for Regions Financial, a 7-fold increase for Wells Fargo and a 6-fold increase for E Trade Financial Corporation.

We observe that the increases of standardized systemic risk betas are mainly due to rising VaRs where in most cases, systemic risk betas are either time-invariant (according to the tests above) or even slightly declining from 2007 to 2008. Hence, companies' *marginal* contribution to the system VaR systemic risk contributions is widely unchanged while their exposure to idiosyncratic risk has been dramatically increased. The first three companies in the 2008 ranking, Regions Financial, AIG and Bank of America, are good examples for companies realizing quite different combinations of marginal systemic contributions and idiosyncratic tail risk levels and thus facing different sources for systemic relevance. In case of Regions Financial, we observe a combination of both a comparably high systemic risk beta and high VaR. Conversely, AIG's *marginal* systemic effect is clearly lower but its potential losses are significantly higher which in turn induce substantial risks for the entire system. Finally, Bank of America reveals the by far highest systemic risk beta in combination with a moderate VaR. This bank is systemically risky due to a high sensitivity of the system to Bank of America's risk exposure though its idiosyncratic risk level is not necessarily alarmingly high.

Bringing moreover together these results with the findings from the network analysis in Section (D.2) yields even deeper insights into the underlying sources of firms' increased systemic importance. In particular, we can identify firms whose increased systemic relevance is mainly due to a strong increase of their idiosyncratic risk as a result of worse fim-specific and macroeconomic conditions in combination with widely unchanged systemic risk betas. For instance, according to our network analysis, Regions Financial does not face significant risk spillovers from other companies and thus exclusively depends on micro- and macroeconomic externalities. As a result, the company's high systemic relevance in 2008 is due to the combination of a moderately high systemic risk beta and severe idiosyncratic risk which in turn affect balance sheets and obligations of other firms. Likewise, Bank of America is not driven by tail risk spillovers from others and is increasingly systemic important exclusively due to firm-specific and macroeconomic conditions.

A second category of firms are institutions whose strong increases of VaRs and thus standardized systemic risk betas are not necessarily only due to economic conditions but likely also due to network effects. According to our framework the latter are included in form of (LASSO-selected) loss exceedances of other firms causing VaRs to jump up whenever corresponding network neighbors get under distress and exceed their (unconditional 10%) loss quantile. These effects are likely being relevant for AIG facing a strong increase of its VaR which in turn receives tail risk spillovers, for instance, from Freddie Mac. Further candidates are, e.g., E Trade Financial, Zions or Morgan Stanley being exposed to substantial tail risk spillovers and realizing strong increases in their VaRs. Finally, we identify companies facing not only rising idiosyncratic risk but also clear variations in their systemic risk betas. A notable case is Fifth Third Bancorporation facing a 15-fold increase in its marginal risk contribution in combination with a tripled VaR. Likewise, also the brokerage Charles Schwab is a company showing strong increases in both VaRs and systemic risk betas.

Hence, though standardized systemic risk betas conveniently condense information on banks' systemic relevance, the underlying driving forces of a bank's changed systemic importance can be quite different. Only simultaneously analyzing and monitoring (i) network effects, (ii) sensitivity to micro- and macroeconomic conditions and (iii) time-variations in systemic risk betas provide deeper insights into the specific role of companies in the network and can build the basis for regulatory measures.

IV. Validity: Pre-Crisis Period

Over 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, these companies could not be included. Nevertheless, to validate and robustify our findings, we perform an additional analysis by re-estimating the model for the time period of January 1, 2000, to June 30, 2007 and including the investment banks Lehman Brothers and Merrill Lynch.

Because of the shorter estimation period, differences between estimated systemic risk contributions are not as pronounced as in the analysis covering the full time period. Therefore, as a sharp ranking of companies might not very meaningful and hard to interpret in this context, Table XII rather categorizes firms into groups with systemic risk contributions of related size. Accordingly, we can distinguish between three broad classes:

Firstly, there are 11 companies with VaRs that significantly influence the system VaR and additionally have comparably large standardized systemic risk beta. The most prominent members of this group are Freddie Mac and JP Morgan. The second group comprises systemically risky companies with significant and positive standardized systemic risk betas mainly clustering around the value 0.02. According to the estimates reported in Table IX, these magnitudes reflect a comparably high systemic relevance. This group contains most of the large depositories and investment banks in our sample including, Bank of America, AIG, Morgan Stanley, among others, but also Lehman Brothers, Merrill Lynch and Fannie Mae. Finally, group 3 includes all companies with either insignificant or even negative (average) systemic risk betas, which are not considered as being systemically risky during the analyzed time period.

In detail, we focus on five 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 might remove some specific features of the data, such as structural changes for *Fannie Mae* and *Freddie Mac* due to their placement under conservatorship by the U.S. government. 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 XII (with the specific companies marked in bold), all of these firms belong to the group of systemically relevant firms.

Table XIII summarizes the results of our empirical analysis for the five 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: While Freddie Mac is not influenced by risk transmission of others, Fannie Mae is driven by loss exceedances of Freddie Mac. TD Ameritrade Holding (AMTD), Charles Schwab (SCHW) and E Trade Financial (ETFC) are large online brokers which operate on the same market as Lehman and Merrill Lynch and are identified as significant tail risk producers. Likewise, we identify bi-directional tail risk dependencies between Lehman and Morgan Stanley, being one of Lehman's main competitors and the second largest investment bank in the U.S. during the estimation period.

All of the five companies of interest have a significant impact on the system. Orders of magnitude of reported standardized systemic risk betas[14] place all of these companies even among the top group of systemically most relevant firms. Focussing particularly on Lehman Brothers and Merrill Lynch, we show the time evolution of their standardized risk betas in Figure 9. Similarly, Figure 10 shows the time series pattern of the respective VaRs. It turns out that the standardized systemic risk beta of Lehman steadily increases from 2005 to 2007. Interestingly, its VaR only increases in the second half of 2005 but remains widely on the same level afterwards. Hence, its growing systemic relevance is mainly due to rising *marginal* effects on the system and is not reflected in Lehman's idiosyncratic risk exposure. The jumps in the VaR (and thus also in the standardized risk beta) are induced by relevant loss exceedances which only occur whenever one of Lehman's tail risk drivers (e.g., Morgan Stanley) exceeds his (unconditional 10%) loss quantile. This discreteness reflects the company's tail risk sensitivity to loss exceedances of competitors.

In case of Merrill Lynch, we observe high levels of both, systemic risk beta and VaR in 2005, followed by a gradual decline until the mid of 2006. However, as for Lehman Brothers, we observe clear differences in the paths of both risk measures in the second half of the period. While the VaR of Merrill Lynch declines even further, its standardized risk beta increases by more than 100% from mid of 2006 to mid of 2007. Hence, also here, the (standardized) systemic risk beta reveals information on the company's systemic importance which cannot be detected by an analysis of the VaR solely. This finding strongly backs the usefulness of our proposed measure.

From these results, which are produced only from pre-crisis data, it is possible to infer that in June 2007, each of the five financial institutions of interest were relevant for the stability of the U.S. financial system. Our findings indicate, firstly, that bailouts during the crisis were justified for Fannie Mae, Freddie Mac and AIG. Also a failure of Merrill Lynch

[14] In case of time-varying betas for Lehman Brothers, Freddie Mac and Merrill Lynch, we report the corresponding time series averages.

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 Morgan Stanley, which in turn is one of the most interconnected companies in our sample, indicates a high risk for contagion as a result of Lehman's failure. Furthermore, our estimates show that Lehman's systemic risk contribution is even slightly higher than that of AIG. Given these results, bailing out the latter but not the former is not necessarily justifiable. If these results had existed in advance, more effective regulatory measures could have been performed possibly reducing the extent of the financial crisis.

V. Conclusion

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

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

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

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

Appendix A. Statistical Large Sample Results

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 $Y_T \leq O_P(r_T)$, for Y_T is 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 nor $K(i)$ 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 $q \in [0,1]$,[15]

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

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

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

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

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

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

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

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

Appendix B. Tables and Figures

Table I: Included financial institutions.

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

* included only in the case study

Table II: Backtest results for VaR^i models. Coverage should be close to the underlying quantile level 0.05. A higher p-value indicates a better model fit in the sense that the model generates a good coverage and conditionally independent VaR-exceedances.

Name	coverage	LR test p-value
Broker Dealers		
E TRADE FINANCIAL	0.041	0.7812
GOLDMAN SACHS GP.	0.05	0.8081
MORGAN STANLEY	0.067	0.1286
CHARLES SCHWAB	0.054	0.661
T ROWE PRICE GP.	0.043	0.5349
Depositories		
BANK OF AMERICA	0.054	0.4907
BB &T	0.054	0.8197
BANK OF NEW YORK MELLON	0.041	0.5557
CITIGROUP	0.045	0.5841
COMERICA	0.043	0.797
HUNTINGTON BCSH.	0.045	0.9471
HUDSON CITY BANC.	0.045	0.6129
JP MORGAN CHASE & CO.	0.045	0.818
MARSHALL & ILSLEY	0.052	0.7088
M & T BK.	0.047	0.4802
NORTHERN TRUST	0.056	0.9682
NY.CMTY.BANC.	0.05	0.9531
PEOPLES UNITED FINANCIAL	0.056	0.3321
PNC FINANCIAL SVS. GP	0.054	0.9863
REGIONS FINANCIAL	0.05	0.9608
SLM	0.058	0.3992
SYNOVUS FINL.	0.041	0.7573
SUNTRUST BANKS	0.056	0.6276
STATE STREET	0.052	0.999
WELLS FARGO & CO	0.047	0.8023
ZIONS BANCORP.	0.043	0.5897
Insurance Companies		
AFLAC	0.052	0.6735
AMERICAN INTL.GP.	0.052	0.3752
ALLSTATE	0.041	0.5207
AON	0.054	0.9437
CHUBB	0.06	0.855
CIGNA	0.056	0.514
CINCINNATI FINL.	0.069	0.4956
CNA FINANCIAL	0.054	0.9321
COVENTRY HEALTH CARE	0.056	0.8685
HARTFORD FINL.SVS.GP.	0.045	0.8125
HEALTH NET	0.045	0.8158
HUMANA	0.058	0.6934
LOEWS	0.045	0.9416
LINCOLN NAT.	0.058	0.4631
MBIA	0.045	0.8158
MARSH & MCLENNAN	0.067	0.6159
PROGRESSIVE OHIO	0.047	0.9732
TORCHMARK	0.047	0.7494
UNUM GROUP	0.045	0.8164
W R BERKLEY	0.052	0.9827
Others		
TD AMERITRADE HOLDING	0.039	0.2879
AMERICAN EXPRESS	0.039	0.8469
FRANKLIN RESOURCES	0.062	0.783
EATON VANCE NV.	0.041	0.7105
FIFTH THIRD BANCORP	0.052	0.9981
FANNIE MAE	0.045	0.7251
FREDDIE MAC	0.047	0.8117
LEGG MASON	0.056	0.826
LEUCADIA NATIONAL	0.052	0.8207
SEI INVESTMENTS	0.054	0.6092
UNION PACIFIC	0.058	0.7084

Table III: Exemplary post-LASSO quantile regressions for VaR^i with $q = 0.05$ for broker dealers and depositories. Regressors were selected by LASSO. Ex.j stands for loss exceedance of company j. For a description of the other regressors, see Section B.

Goldman Sachs				
	Value	Std. Error	t-value	p-value
(Intercept)	0.0281	0.0282	0.9963	0.3196
Ex.AIG	-0.0842	0.1520	-0.5537	0.5800
Ex.MS	-0.4974	0.0787	-6.3186	0.0000
LEV	0.0017	0.0010	1.7860	0.0748
housing	0.0001	0.0002	0.9030	0.3670
vix	0.0020	0.0005	3.8849	0.0001

Morgan Stanley				
	Value	Std. Error	t-ratio	p-value
(Intercept)	-0.0476	0.0490	-0.9721	0.3315
Ex.AIG	-0.1570	0.0239	-6.5597	0.0000
Ex.BAC	-0.5824	0.2016	-2.8885	0.0041
Ex.CNA	-0.3295	0.2683	-1.2280	0.2201
Ex.ETFC	-0.0779	0.0834	-0.9339	0.3509
Ex.EV	-0.1774	0.1585	-1.1192	0.2637
Ex.GS	-0.4743	0.1449	-3.2742	0.0011
Ex.LM	0.0472	0.1120	0.4215	0.6736
Ex.LNC	0.0734	0.2459	0.2983	0.7656
Ex.SCHW	-0.3780	0.1446	-2.6138	0.0093
Ex.SEIC	-0.1974	0.1281	-1.5412	0.1240
LEV	-0.0003	0.0014	-0.2229	0.8237
BM	-0.0045	0.0130	-0.3465	0.7291
housing	0.0002	0.0002	1.4985	0.1347
vix	0.0002	0.0009	0.2352	0.8142
repo	-0.0017	0.0248	-0.0699	0.9443
credit	0.1051	0.0572	1.8360	0.0670

JP Morgan				
	Value	Std. Error	t-ratio	p-value
(Intercept)	-0.0128	0.0150	-0.8513	0.3950
Ex.C	-0.3992	0.1992	-2.0046	0.0456
Ex.GS	-0.2628	0.1461	-1.7985	0.0728
Ex.SCHW	-0.2366	0.0747	-3.1669	0.0016
BM	-0.0200	0.0145	-1.3789	0.1686
housing	0.0000	0.0001	0.2900	0.7719
vix	0.0024	0.0006	4.3071	0.0000

Bank of New York Mellon				
	Value	Std. Error	t-ratio	p-value
(Intercept)	-0.0235	0.0158	-1.4902	0.1369
Ex.AXP	-0.0654	0.0862	-0.7586	0.4485
Ex.BBT	-0.1990	0.1346	-1.4781	0.1401
Ex.FNM	-0.0106	0.0639	-0.1655	0.8686
Ex.GS	-0.1104	0.1341	-0.8232	0.4108
Ex.HIG	0.1311	0.0878	1.4932	0.1361
Ex.JPM	-0.0986	0.0710	-1.3873	0.1660
Ex.L	-0.2383	0.1506	-1.5828	0.1142
Ex.MS	0.0541	0.1059	0.5110	0.6096
Ex.NTRS	-0.3676	0.1053	-3.4913	0.0005
Ex.SNV	-0.3211	0.1398	-2.2967	0.0221
Ex.STT	-0.1980	0.1594	-1.2425	0.2147
Ex.TROW	-0.1208	0.1149	-1.0517	0.2935
LEV	0.0001	0.0013	0.0875	0.9303
housing	0.0001	0.0001	0.9721	0.3315
vix	0.0005	0.0005	0.9871	0.3241
repo	-0.0150	0.0121	-1.2365	0.2169
term	0.0094	0.0155	0.6091	0.5428

Table IV: Exemplary post-LASSO quantile regressions for VaR^i with $q = 0.05$ for insurance companies and others. Regressors were selected by LASSO. Ex.j stands for loss exceedance of company j. For a description of the other regressors, see Section B.

American International Group				
	Value	Std. Error	t-ratio	p-value
(Intercept)	0.0803	0.0708	1.1345	0.2572
Ex.FRE	-0.1719	0.4867	-0.3532	0.7241
Ex.MMC	-0.5127	0.2553	-2.0079	0.0452
LEV	0.0081	0.0067	1.2064	0.2283
BM	0.0340	0.0138	2.4611	0.0142
housing	-0.0003	0.0002	-1.3616	0.1740
vix	0.0022	0.0011	2.0514	0.0408

CNA Financial				
	Value	Std. Error	t-ratio	p-value
(Intercept)	-0.0257	0.0241	-1.0673	0.2864
Ex.HIG	-0.4179	0.2805	-1.4899	0.1369
Ex.MBI	-0.6330	0.1677	-3.7738	0.0002
LEV	0.0018	0.0040	0.4362	0.6629
BM	-0.0038	0.0121	-0.3099	0.7568
housing	0.0001	0.0002	0.1857	0.8527
vix	0.0003	0.0007	0.4478	0.6545

Fannie Mae				
	Value	Std. Error	t-value	p-value
(Intercept)	-0.0504	0.0093	-5.4426	0.0000
Ex.C	-0.0972	0.2161	-0.4497	0.6531
Ex.FRE	-0.9086	0.0097	-93.6342	0.0000
Ex.JPM	-0.2234	0.1814	-1.2313	0.2189
Ex.MS	-0.0562	0.2195	-0.2560	0.7981
Y.t.FNM.lag	-0.0348	0.0270	-1.2887	0.1982
LEV	-0.0002	0.0003	-0.5946	0.5524
BM	-0.0032	0.0051	-0.6199	0.5357
housing	0.0001	0.0001	1.0453	0.2964
vix	-0.0001	0.0005	-0.1534	0.8781
repo	0.0780	0.0238	3.2730	0.0011

SEI Investments				
	Value	Std. Error	t-ratio	p-value
(Intercept)	0.3706	0.3337	1.1105	0.2673
Ex.MS	-0.5054	0.2634	-1.9188	0.0556
SIZE	0.0164	0.0144	1.1442	0.2531
housing	0.0004	0.0002	2.2166	0.0271
vix	0.0029	0.0010	2.8148	0.0051

Table V: Summary statistics for estimated individual time series of VaR^i.

Name	Mean	Standard dev.	Min	10% quant.	90% quant.	Max.
		Broker Dealers				
E TRADE FINANCIAL	0.108	0.066	0.046	0.062	0.172	0.809
GOLDMAN SACHS GP.	0.061	0.038	0.033	0.041	0.092	0.573
MORGAN STANLEY	0.068	0.065	0.020	0.036	0.119	0.905
CHARLES SCHWAB	0.094	0.045	0.041	0.055	0.140	0.335
T ROWE PRICE GP.	0.062	0.042	0.035	0.039	0.091	0.583
BANK OF AMERICA	0.062	0.037	0.023	0.031	0.100	0.270
		Depositories				
BB &T	0.058	0.027	0.015	0.031	0.093	0.192
BANK OF NEW YORK MELLON	0.047	0.033	-0.051	0.029	0.076	0.269
CITIGROUP	0.055	0.062	0.024	0.028	0.098	0.926
COMERICA	0.055	0.037	0.023	0.031	0.080	0.392
HUNTINGTON BCSH.	0.076	0.044	0.010	0.026	0.142	0.245
HUDSON CITY BANC.	0.040	0.015	0.023	0.028	0.055	0.132
JP MORGAN CHASE & CO.	0.060	0.045	0.023	0.027	0.094	0.561
MARSHALL & ILSLEY	0.071	0.028	0.024	0.037	0.111	0.134
M & T BK.	0.049	0.023	0.024	0.031	0.069	0.316
NORTHERN TRUST	0.067	0.028	0.032	0.042	0.094	0.224
NY.CMTY.BANC.	0.057	0.034	0.030	0.040	0.094	0.374
PEOPLES UNITED FINANCIAL	0.048	0.021	0.005	0.027	0.077	0.123
PNC FINANCIAL SVS. GP	0.052	0.043	0.011	0.025	0.084	0.645
REGIONS FINANCIAL	0.076	0.079	0.021	0.029	0.118	0.420
SLM	0.065	0.059	0.032	0.036	0.112	0.528
SYNOVUS FINL.	0.052	0.041	-0.021	0.025	0.081	0.412
SUNTRUST BANKS	0.060	0.046	0.021	0.032	0.106	0.615
STATE STREET	0.068	0.032	0.028	0.036	0.101	0.245
WELLS FARGO & CO	0.044	0.038	0.015	0.021	0.073	0.439
ZIONS BANCORP.	0.071	0.053	0.015	0.028	0.140	0.331
		Insurance Companies				
AFLAC	0.052	0.048	0.029	0.035	0.077	0.643
AMERICAN INTL.GP.	0.078	0.103	0.020	0.033	0.111	0.691
ALLSTATE	0.045	0.048	0.000	0.027	0.076	0.781
AON	0.045	0.044	0.010	0.025	0.078	0.565
CHUBB	0.048	0.031	0.019	0.024	0.072	0.336
CIGNA	0.065	0.055	0.031	0.035	0.097	0.701
CINCINNATI FINL.	0.040	0.029	0.007	0.023	0.063	0.372
CNA FINANCIAL	0.058	0.063	0.036	0.037	0.087	0.653
COVENTRY HEALTH CARE	0.087	0.089	0.027	0.034	0.159	0.875
HARTFORD FINL.SVS.GP.	0.083	0.163	0.029	0.034	0.151	2.509
HEALTH NET	0.088	0.029	0.047	0.058	0.118	0.238
HUMANA	0.075	0.048	0.042	0.050	0.108	0.570
LOEWS	0.051	0.025	0.014	0.025	0.077	0.183
LINCOLN NAT.	0.057	0.066	0.007	0.022	0.093	1.005
MBIA	0.100	0.122	0.030	0.043	0.220	1.670
MARSH & MCLENNAN	0.058	0.066	0.009	0.028	0.106	0.598
PROGRESSIVE OHIO	0.064	0.031	0.020	0.031	0.112	0.204
TORCHMARK	0.054	0.033	0.016	0.021	0.100	0.199
UNUM GROUP	0.080	0.069	0.023	0.038	0.134	0.835
W R BERKLEY	0.052	0.019	0.023	0.036	0.073	0.271
		Others				
TD AMERITRADE HOLDING	0.098	0.062	-0.026	0.045	0.181	0.454
AMERICAN EXPRESS	0.049	0.041	0.009	0.019	0.088	0.416
FRANKLIN RESOURCES	0.053	0.035	0.029	0.036	0.079	0.427
EATON VANCE NV.	0.054	0.033	0.007	0.037	0.076	0.477
FIFTH THIRD BANCORP	0.082	0.073	0.015	0.030	0.149	0.476
FANNIE MAE	0.077	0.126	0.019	0.038	0.107	2.253
FREDDIE MAC	0.079	0.174	0.033	0.039	0.092	3.233
LEGG MASON	0.081	0.050	0.034	0.045	0.122	0.72
LEUCADIA NATIONAL	0.044	0.037	0.020	0.023	0.073	0.419
SEI INVESTMENTS	0.072	0.040	0.034	0.044	0.106	0.553
UNION PACIFIC	0.056	0.021	0.027	0.036	0.08	0.187

Table VI: Tail risk cross dependencies: Loss exceedances of companies on the right hand-side have been selected by LASSO as regressors for the VaR^i-model (q=0.05) of companies on the left hand-side.

Name	Influencing companies
	Broker Dealers
E TRADE FINANCIAL	AMTD, C, FNM, MS
GOLDMAN SACHS GP.	AIG, MS
MORGAN STANLEY	AIG, BAC, CNA, ETFC, EV, GS, LM, LNC, SCHW, SEIC
CHARLES SCHWAB	AMTD
T ROWE PRICE GP.	HIG, LM, MBI, MS
	Depositories
BANK OF AMERICA	
BB &T	
BANK OF NEW YORK MELLON	AXP, BBT, FNM, GS, HIG, JPM, L, MS, NTRS, SNV, STT, TROW
CITIGROUP	ETFC, HIG, JPM, LNC, MBI
COMERICA	FRE, HBAN, MBI, MS, RF
HUNTINGTON BCSH.	
HUDSON CITY BANC.	
JP MORGAN CHASE & CO.	C, GS, SCHW
MARSHALL & ILSLEY	
M & T BK.	MS
NORTHERN TRUST	
NY.CMTY.BANC.	HIG, LNC, PBCT
PEOPLES UNITED FINANCIAL	
PNC FINANCIAL SVS. GP	C
REGIONS FINANCIAL	
SLM	ETFC, FNM, LNC, MBI
SYNOVUS FINL.	CMA, FITB, FRE, RF, ZION
SUNTRUST BANKS	LNC
STATE STREET	
WELLS FARGO & CO	BAC, C, FNM, LNC, MBI, STI
ZIONS BANCORP.	
	Insurance Companies
AFLAC	HIG
AMERICAN INTL.GP.	FRE, MMC
ALLSTATE	CNA, CVH, LNC, MS, UNM
AON	AMTD, CMA, HBAN, MBI, MS, RF, STI, UNM
CHUBB	AMTD, EV, HBAN, HIG, MBI, UNM
CIGNA	CVH, HIG, LNC, MS
CINCINNATI FINL.	AXP, CMA, CNA, CVH, HIG, LM, MBI, TROW
CNA FINANCIAL	HIG, MBI
COVENTRY HEALTH CARE	CI, FITB, HNT, HUM, MMC, SEIC
HARTFORD FINL.SVS.GP.	LNC
HEALTH NET	
HUMANA	CVH, LNC, UNM
LOEWS	
LINCOLN NAT.	C, HIG, MS
MBIA	FRE
MARSH & MCLENNAN	AXP, JPM, MI, MS, SCHW, SEIC, TROW, UNM
PROGRESSIVE OHIO	
TORCHMARK	
UNUM GROUP	HIG
W R BERKLEY	MS, UNM
	Others
TD AMERITRADE HOLDING	AON, ETFC, MBI, RF, SCHW, TROW, UNM
AMERICAN EXPRESS	AMTD, BBT, ETFC, EV, HIG, LNC, MBI, SCHW, STT
FRANKLIN RESOURCES	AMTD, HIG, LM, LNC, MBI, UNM
EATON VANCE NV.	CB, HBAN, LM, LNC, MS, SEIC, SLM, UNM
FIFTH THIRD BANCORP	
FANNIE MAE	C, FRE, JPM, MS
FREDDIE MAC	FNM
LEGG MASON	MS
LEUCADIA NATIONAL	C, CVH, ETFC, MBI, SEIC
SEI INVESTMENTS	MS
UNION PACIFIC	ETFC, HIG

Table VII: Estimates of parameters $\beta_0^{s|i}$ and $\boldsymbol{\eta}^{s|i}$ and p-values for the test on systemic relevance (joint significance of $\widehat{VaR}_t^i$ and $\widehat{VaR}_t^i \cdot \mathbf{Z}_{t-1}^i$, Hypothesis H1) with $\mathbf{Z}_{t-1}^i = (MMM_{t-1}, SIZE_{t-1}, LEV_{t-1})'$ and for the test on time-variations of systemic risk betas (significance of $\widehat{VaR}_t^i \cdot \mathbf{Z}_{t-1}^i$, Hypothesis H2).

Name	$\hat{\beta}_0^{s\|i}$	$\hat{\eta}_{MMM}^{s\|i}$	$\hat{\eta}_{SIZE}^{s\|i}$	$\hat{\eta}_{LEV}^{s\|i}$	pv_{H1}	pv_{H2}
Systemically relevant companies with time-varying $\beta_t^{s\|i}$						
AMERICAN EXPRESS	-6.284	0.195	0.278	-0.087	0.001	0.024
AMERICAN INTL.GP.	-0.276	-2.352	0.078	-0.008	0.004	0.023
BANK OF AMERICA	-41.872	15.230	1.140	0.043	0.016	0.007
CHARLES SCHWAB	9.824	1.453	-0.457	0.165	0.000	0.000
CINCINNATI FINL.	-18.766	2.370	0.820	-0.623	0.008	0.005
COMERICA	4.775	1.038	-0.170	-0.088	0.012	0.012
E TRADE FINANCIAL	-0.549	-0.088	0.028	0.009	0.013	0.068
EATON VANCE NV.	0.083	-0.520	0.013	-0.054	0.000	0.017
FIFTH THIRD BANCORP	0.828	3.978	-0.178	0.076	0.022	0.027
FRANKLIN RESOURCES	-3.201	0.746	0.136	0.201	0.002	0.007
HARTFORD FINL.SVS.GP.	-1.556	0.132	0.059	-0.005	0.017	0.004
HUDSON CITY BANC.	-55.089	-0.336	2.010	-0.206	0.004	0.005
HUNTINGTON BCSH.	-7.751	4.295	0.255	-0.267	0.035	0.048
LEGG MASON	3.664	-0.091	-0.158	-0.019	0.020	0.005
NORTHERN TRUST	-16.221	-1.229	0.397	0.331	0.017	0.010
NY.CMTY.BANC.	-3.918	-1.383	0.196	0.020	0.007	0.009
PROGRESSIVE OHIO	-0.976	2.264	-0.220	1.096	0.001	0.001
SLM	-2.677	0.091	0.115	-0.006	0.001	0.018
STATE STREET	-29.239	0.319	1.086	-0.011	0.007	0.015
SUNTRUST BANKS	-2.692	1.424	0.088	-0.048	0.100	0.057
T ROWE PRICE GP.	5.256	0.471	-0.194	-0.506	0.013	0.069
UNION PACIFIC	9.511	-3.012	-0.271	-0.354	0.010	0.005
UNUM GROUP	-4.424	1.434	0.174	-0.134	0.066	0.078
Systemically relevant companies with constant $\beta^{s\|i}$						
AON	-2.170	0.250	0.093	-0.007	0.002	0.606
CITIGROUP	-1.406	-0.143	0.052	0.015	0.021	0.513
CNA FINANCIAL	-4.609	-0.525	0.207	0.011	0.028	0.629
COVENTRY HEALTH CARE	-0.031	-0.379	-0.018	0.299	0.038	0.440
JP MORGAN CHASE & CO.	6.671	-3.174	-0.161	0.028	0.015	0.200
LEUCADIA NATIONAL	6.281	-0.332	-0.259	-0.136	0.015	0.064
LINCOLN NAT.	-2.798	0.374	0.117	-0.016	0.043	0.159
MORGAN STANLEY	1.702	0.722	-0.072	0.003	0.002	0.670
PNC FINANCIAL SVS. GP	3.564	-0.233	-0.108	-0.029	0.075	0.619
REGIONS FINANCIAL	-2.703	4.349	0.012	-0.044	0.081	0.422
TORCHMARK	-25.555	5.501	0.828	0.195	0.082	0.120
WELLS FARGO & CO	-6.158	2.252	0.168	0.018	0.013	0.120
ZIONS BANCORP.	-2.892	12.997	-0.255	-0.047	0.049	0.101
No significant influence						
AFLAC	-7.339	8.078	0.099	-0.197	0.145	
ALLSTATE	-2.933	3.427	0.003	0.028	0.145	
BANK OF NEW YORK MELLON	1.094	0.083	-0.038	-0.006	0.373	
BB &T	-29.215	9.828	0.977	0.204	0.204	
CHUBB	-4.724	0.388	0.167	0.057	0.708	
CIGNA	2.173	1.147	-0.129	0.001	0.479	
FANNIE MAE	-0.508	-0.036	0.018	0.001	0.446	
FREDDIE MAC	-5.977	-0.514	0.226	-0.006	0.198	
GOLDMAN SACHS GP.	-8.046	1.209	0.283	-0.023	0.124	
HEALTH NET	-2.620	3.060	-0.063	0.248	0.229	
HUMANA	0.735	-0.681	-0.042	0.116	0.339	
LOEWS	17.257	-2.698	-0.449	-0.204	0.320	
M & T BK.	-3.37	-3.296	0.168	0.135	0.149	
MARSH & MCLENNAN	1.148	0.415	-0.053	0.012	0.410	
MARSHALL & ILSLEY	5.490	-3.533	-0.235	0.250	0.227	
MBIA	-0.580	0.153	0.033	-0.008	0.167	
PEOPLES UNITED FINANCIAL	15.921	0.302	-0.690	-0.046	0.233	
SEI INVESTMENTS	-1.365	0.006	0.062	-0.029	0.878	
SYNOVUS FINL.	-0.111	-0.297	0.044	-0.047	0.619	
TD AMERITRADE HOLDING	0.492	-0.089	-0.013	-0.005	0.309	
W R BERKLEY	1.437	2.086	-0.077	-0.116	0.648	

Table VIII: Estimates of time-invariant systemic risk betas $\beta^{s|i}$ for the cases where the hypothesis of no time variation $\boldsymbol{\eta}^{s|i} \neq 0$ could not be rejected (see the last column in Table VII)

Name	$\hat{\beta}^{s\|i}$	p-value
AON	0.257	0.000
CITIGROUP	0.287	0.036
CNA FINANCIAL	0.218	0.013
COVENTRY HEALTH CARE	0.118	0.011
JP MORGAN CHASE & CO.	0.311	0.006
LEUCADIA NATIONAL	0.109	0.088
LINCOLN NAT.	0.179	0.018
MORGAN STANLEY	0.207	0.000
PNC FINANCIAL SVS. GP	0.291	0.070
REGIONS FINANCIAL	0.448	0.033
TORCHMARK	0.236	0.361
WELLS FARGO & CO	0.181	0.022
ZIONS BANCORP.	0.380	0.096

Table IX: Ranking of average systemic risk contributions based on standardized systemic risk betas. The third column lists loss exceedances that are included in the respective company's VaR^i-regression. Estimation period 2000-2008.

Rank	Name	$\widehat{\beta}^{s\|i}_{av}$	influencing companies
1	BANK OF AMERICA	0.0873	
2	UNION PACIFIC	0.0351	ETFC, HIG
3	REGIONS FINANCIAL	0.0341	
4	ZIONS BANCORP.	0.0268	
5	E TRADE FINANCIAL	0.0230	AMTD, C, FRE, MBI, MS, SCHW
6	CHARLES SCHWAB	0.0209	AMTD
7	JP MORGAN CHASE	0.0187	C, GS, SCHW
8	AMERICAN EXPRESS	0.0172	AMTD, BBT, ETFC, EV, HIG, LNC, MBI, SCHW, STT
9	EATON VANCE NV.	0.0161	CB, HBAN, LM, LNC, MS, SEIC, SLM, UNM
10	CITIGROUP	0.0158	ETFC, HIG, JPM, LNC, MBI
11	PNC FINANCIAL SVS. GP	0.0152	C
12	MORGAN STANLEY	0.0142	AIG, BAC, CNA, ETFC, EV, GS, LM, LNC, SCHW, SEIC
13	SLM	0.0133	ETFC, FNM, LNC, MBI
14	COMERICA	0.0129	FRE, HBAN, MBI, MS, RF
15	CNA FINANCIAL	0.0125	HIG, MBI
16	AON	0.0117	AMTD, CMA, HBAN, MBI, MS, RF, STI, UNM
17	AMERICAN INTL.GP.	0.0113	FRE, MMC
18	COVENTRY HEALTH CARE	0.0102	CI, FITB, HNT, HUM, MMC, SEIC
19	LINCOLN NAT.	0.0102	C, HIG, MS
20	FRANKLIN RESOURCES	0.0099	AMTD, HIG, LM, LNC, MBI, UNM
21	NY.CMTY.BANC.	0.0098	HIG, LNC, PBCT
22	T ROWE PRICE GP.	0.0096	HIG, LM, MBI, MS
23	WELLS FARGO & CO.	0.0079	BAC, C, FNM, LNC, MBI, STI
24	SUNTRUST BANKS	0.0074	LNC
25	CINCINNATI FINL.	0.0071	AXP, CMA, CNA, CVH, HIG, LM, MBI, TROW
26	FIFTH THIRD BANCORP	0.0057	
27	LEUCADIA NATIONAL	0.0053	C, CVH, ETFC, MBI, SEIC
28	HARTFORD FINL.SVS.GP.	0.0005	LNC

Table X: Ranking of systemic risk contributions based on estimated standardized systemic risk betas ($\widehat{\overline{\beta}}_t^{s|i}$), end of May 2007 (before the beginning of the financial crisis). Estimated systemic risk betas and VaRs are listed in addition, to illustrate the different sources of variation in $\widehat{\overline{\beta}}_t^{s|i}$.

Rank	Name	$\widehat{\overline{\beta}}_{2007}^{s\|i}$	$\hat{\beta}_{2007}^{s\|i}$	$\widehat{VaR}_{2007}^{i}$
1	BANK OF AMERICA	0.0645	1.6068	0.0401
2	UNION PACIFIC	0.0441	0.7466	0.0590
3	CHARLES SCHWAB	0.0262	0.3247	0.0807
4	ZIONS BANCORP.	0.0179	0.3795	0.0472
5	EATON VANCE NV.	0.0163	0.3280	0.0496
6	E TRADE FINANCIAL	0.0154	0.2397	0.0644
7	REGIONS FINANCIAL	0.0150	0.4477	0.0336
8	AMERICAN EXPRESS	0.0149	0.3688	0.0403
9	SLM	0.0142	0.2498	0.0567
10	AMERICAN INTL.GP.	0.0104	0.2471	0.0421
11	JP MORGAN CHASE	0.0100	0.3107	0.0323
12	CITIGROUP	0.0100	0.2875	0.0348
13	NY.CMTY.BANC.	0.0099	0.2268	0.0436
14	FRANKLIN RESOURCES	0.0094	0.2349	0.0402
15	PNC FINANCIAL SVS. GP	0.0094	0.2907	0.0324
16	AON	0.0089	0.2573	0.0347
17	MORGAN STANLEY	0.0088	0.2070	0.0425
18	CNA FINANCIAL	0.0084	0.2177	0.0385
19	CINCINNATI FINL.	0.0079	0.2252	0.0353
20	SUNTRUST BANKS	0.0076	0.2197	0.0346
21	COMERICA	0.0057	0.1954	0.0292
22	WELLS FARGO & CO	0.0051	0.1806	0.0283
23	LEUCADIA NATIONAL	0.0051	0.1365	0.0373
24	LINCOLN NAT.	0.0038	0.1795	0.0211
25	COVENTRY HEALTH CARE	0.0034	0.1176	0.0292
26	UNUM GROUP	0.0026	0.0849	0.0309
27	HARTFORD FINL.SVS.GP.	0.0019	0.0535	0.0363
28	T ROWE PRICE GP.	0.0014	0.0327	0.0432
29	FIFTH THIRD BANCORP	0.0011	0.0177	0.0604

Table XI: Ranking of systemic risk contributions based on estimated standardized systemic risk betas ($\widehat{\overline{\beta}}_t^{s|i}$), end of September 2008 (at the height of the financial crisis). Estimated systemic risk betas and VaRs are listed in addition, to illustrate the different sources of variation in $\widehat{\overline{\beta}}_t^{s|i}$.

Rank	Name	$\widehat{\overline{\beta}}_{2008}^{s\|i}$	$\hat{\beta}_{2008}^{s\|i}$	$\widehat{VaR}_{2008}^{i}$
1	REGIONS FINANCIAL	0.1503	0.4477	0.3356
2	AMERICAN INTL.GP.	0.1316	0.1903	0.6911
3	BANK OF AMERICA	0.1205	1.2287	0.0980
4	E TRADE FINANCIAL	0.1004	0.2504	0.4011
5	ZIONS BANCORP.	0.0589	0.3795	0.1551
6	FIFTH THIRD BANCORP	0.0575	0.2628	0.2189
7	SLM	0.0496	0.1377	0.3599
8	UNION PACIFIC	0.0480	0.6369	0.0753
9	CNA FINANCIAL	0.0423	0.2177	0.1941
10	WELLS FARGO & CO	0.0362	0.1806	0.2006
11	CHARLES SCHWAB	0.0315	0.5805	0.0542
12	MORGAN STANLEY	0.0251	0.2070	0.1211
13	PNC FINANCIAL SVS. GP	0.0235	0.2907	0.0807
14	JP MORGAN CHASE	0.0208	0.3107	0.0669
15	AON	0.0183	0.2573	0.0713
16	EATON VANCE NV.	0.0176	0.2774	0.0634
17	CITIGROUP	0.0172	0.2875	0.0600
18	AMERICAN EXPRESS	0.0170	0.3196	0.0532
19	COMERICA	0.0150	0.1046	0.1436
20	SUNTRUST BANKS	0.0150	0.1372	0.1094
21	COVENTRY HEALTH CARE	0.0141	0.1176	0.1202
22	LINCOLN NAT.	0.0134	0.1795	0.0749
23	FRANKLIN RESOURCES	0.0124	0.1572	0.0790
24	NY.CMTY.BANC.	0.0115	0.2264	0.0507
25	T ROWE PRICE GP.	0.0049	0.0313	0.1556
26	UNUM GROUP	0.0042	0.0671	0.0624
27	LEUCADIA NATIONAL	0.0009	0.0081	0.1056

Table XII: Group ranking of systemic risk contributions for the pre-crisis period 2000 - mid 2007. The upper part, group 1, contains companies with significant $\beta_t^{s|i}$ and high $\hat{\overline{\beta}}_{av}^{s|i}$. The middle part (group 2) lists companies with positive and significant $\beta_t^{s|i}$, but smaller $\hat{\overline{\beta}}_{av}^{s|i}$. Group 3 includes companies not determined to be systemically risky during the estimation period, i.e., those with insignificant or negative systemic risk betas. Case study companies are marked in bold.

Systemic risk contributions	Companies
Group 1, $\hat{\overline{\beta}}_{av}^{s\|i} \in [0.034, 0.084]$	JPM, **FRE**, AXP, BBT, MTB, CINF, AFL, CVH, SLM, STI, LM
Group 2, $\hat{\overline{\beta}}_{av}^{s\|i} \in [0.004, 0.030]$	BAC, C, **AIG**, MS, **LEH**, WFC, **FNM**, MBI, PGR, **ML**, BK, AON, TROW, LUK, ETFC, WRB, NYB, ALL, SNV, BEN, CB, TMK, LNC, UNM, AMTD, MI
Group 3	CMA, CNA, HBAN, L, SCHW, PNC, RF, STT, UNP, HNT, NTRS, EV, GS, ZION, HUM, FITB, SEIC, HIG, PBCT, CI, HCBK, MMC

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

Name	inclucenced by	influences	overall sign.	average $\widehat{\overline{\beta}}_t^{s\|i}$	average $\widehat{\beta}_t^{s\|i}$
FREDDIE		FNM	0.004*	0.078	1.389
MERRILL	AMTD		0.000*	0.026	1.472
LEHMAN	AMTD, MS, SCHW	GS, MS	0.009*	0.030	0.375
FANNIE	FRE	SLM	0.011	0.021	0.406
AIG	ETFC, MMC	ALL, BK, CB	0.025	0.021	0.403

*time-varying betas

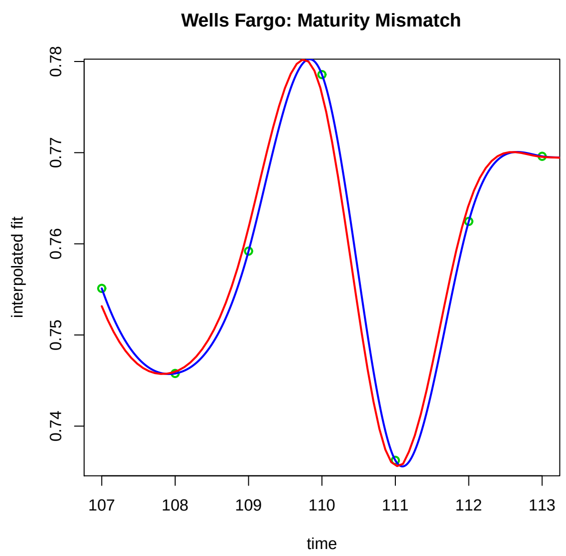

Figure 4: Illustration of interpolated maturity mismatch times for Wells Fargo. Green: actual data points, blue: interpolation spline, red: weekly aggregates.

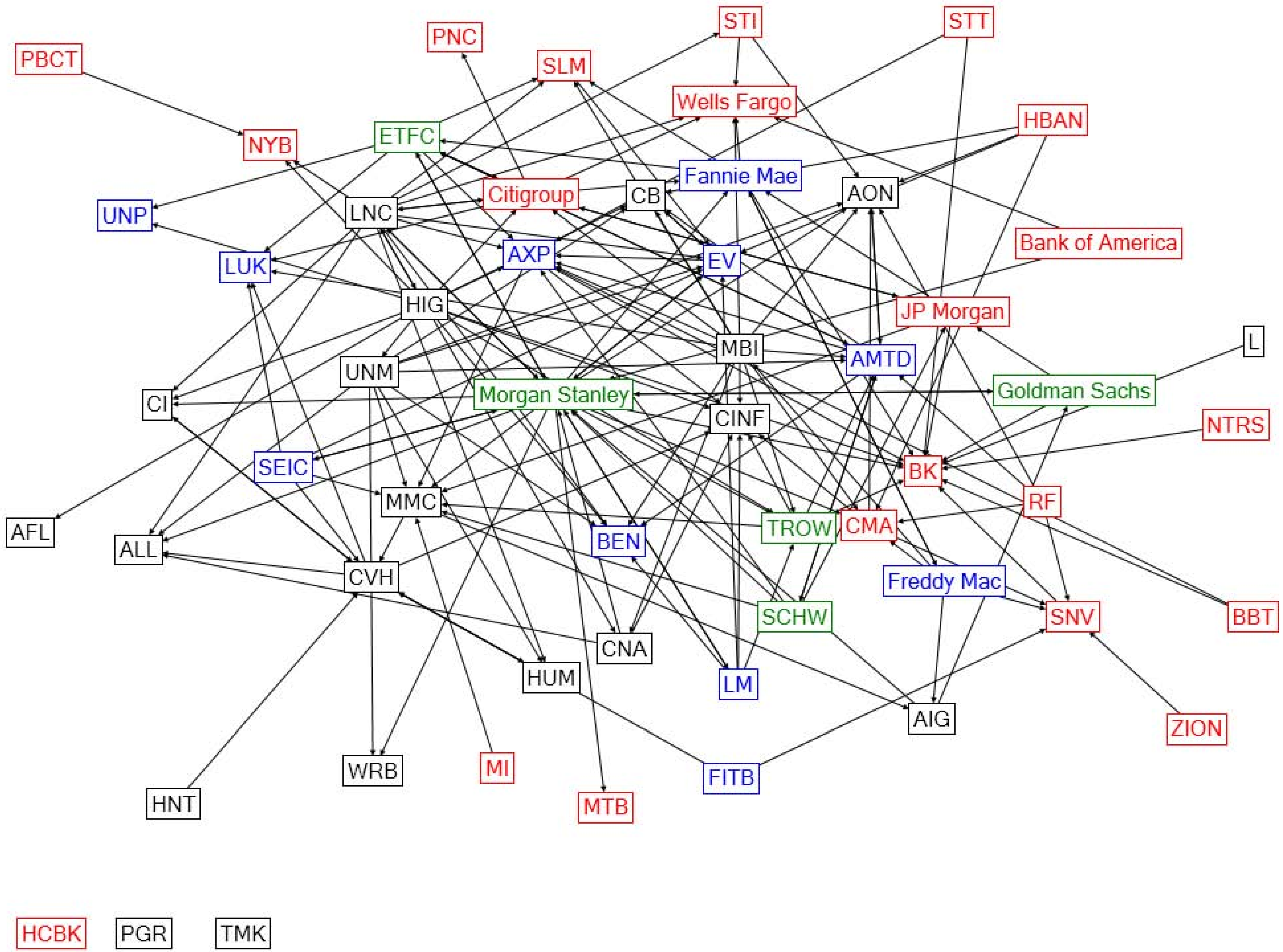

Figure 5: Full network graph for the system of the 57 largest financial companies in the U.S. For simplicity, arrows only mark risk spillovers effects without referring to their respective size. Otherwise arrows and colors are as defined in Figure 1. A complete list of firms' acronyms is contained in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

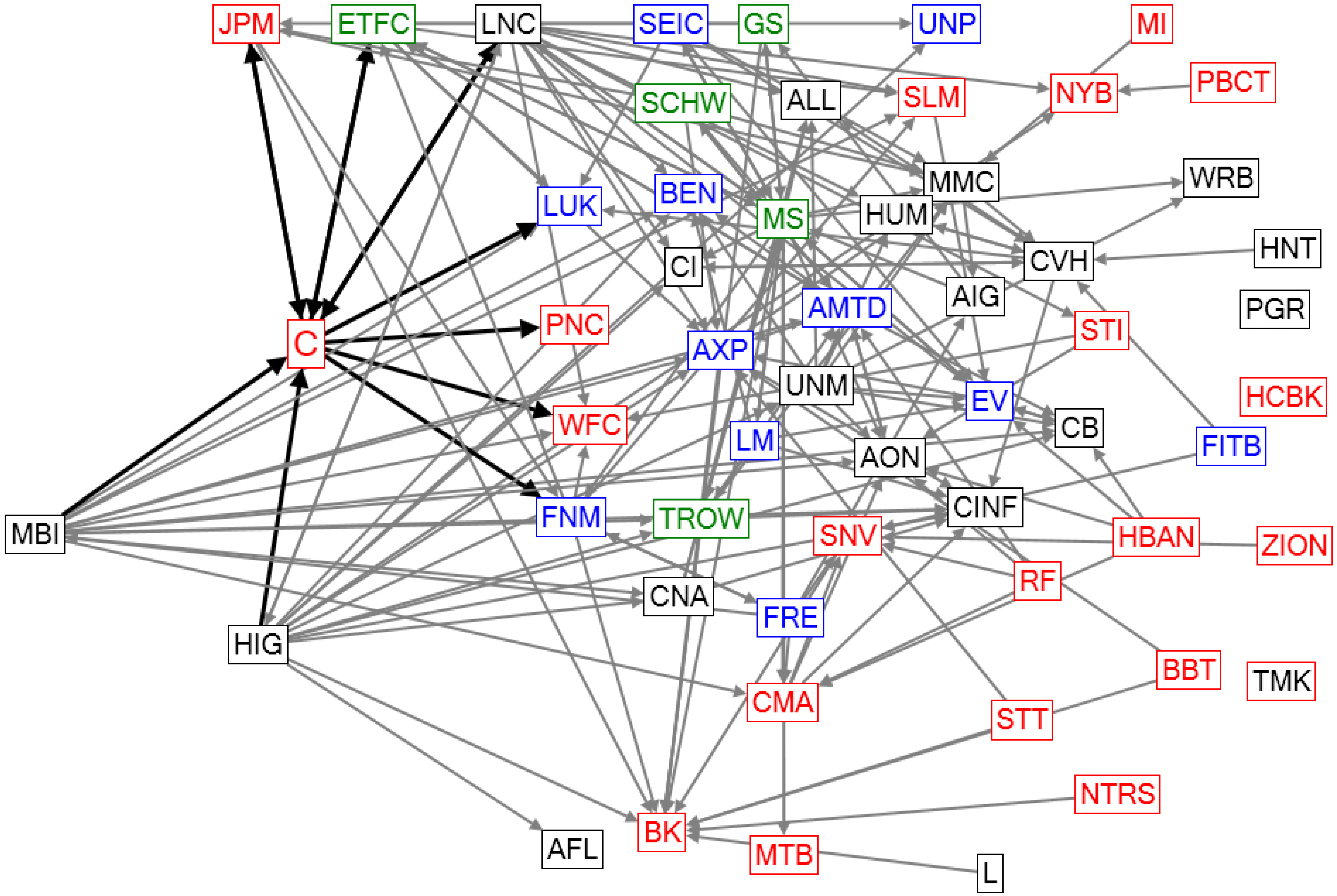

Figure 6: Full Network graph of Citigroup (C) graphically highlighting risk drivers and risk recipients directly connected to Citigroup with bold arrows. Arrows, colors and acronyms are as in Figure 5.

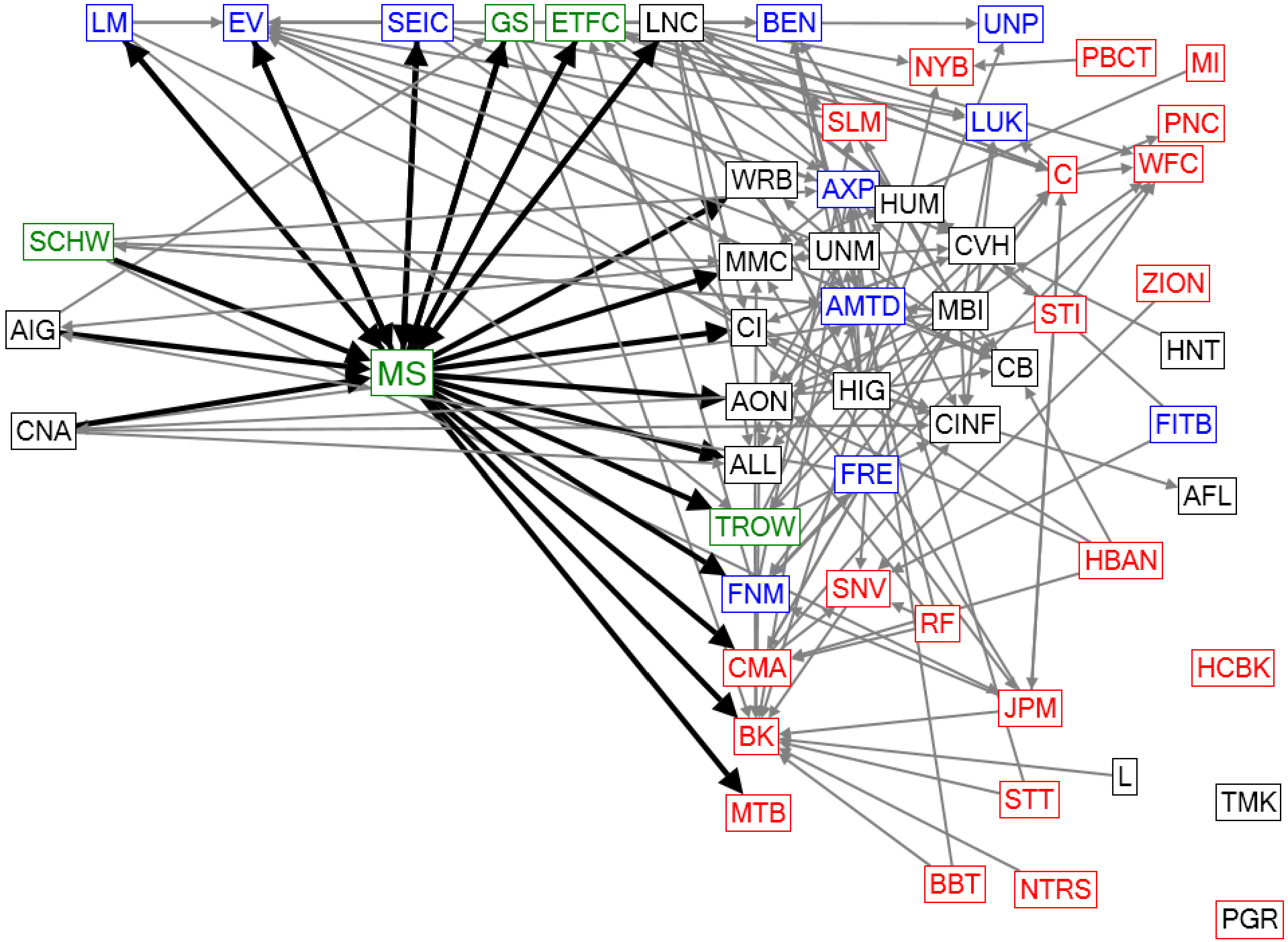

Figure 7: Full Network graph of Morgan Stanley (MS) highlighting risk drivers and risk recipients directly connected to Morgan Stanley with bold arrows. Arrows, colors and acronyms are as in Figure 5.

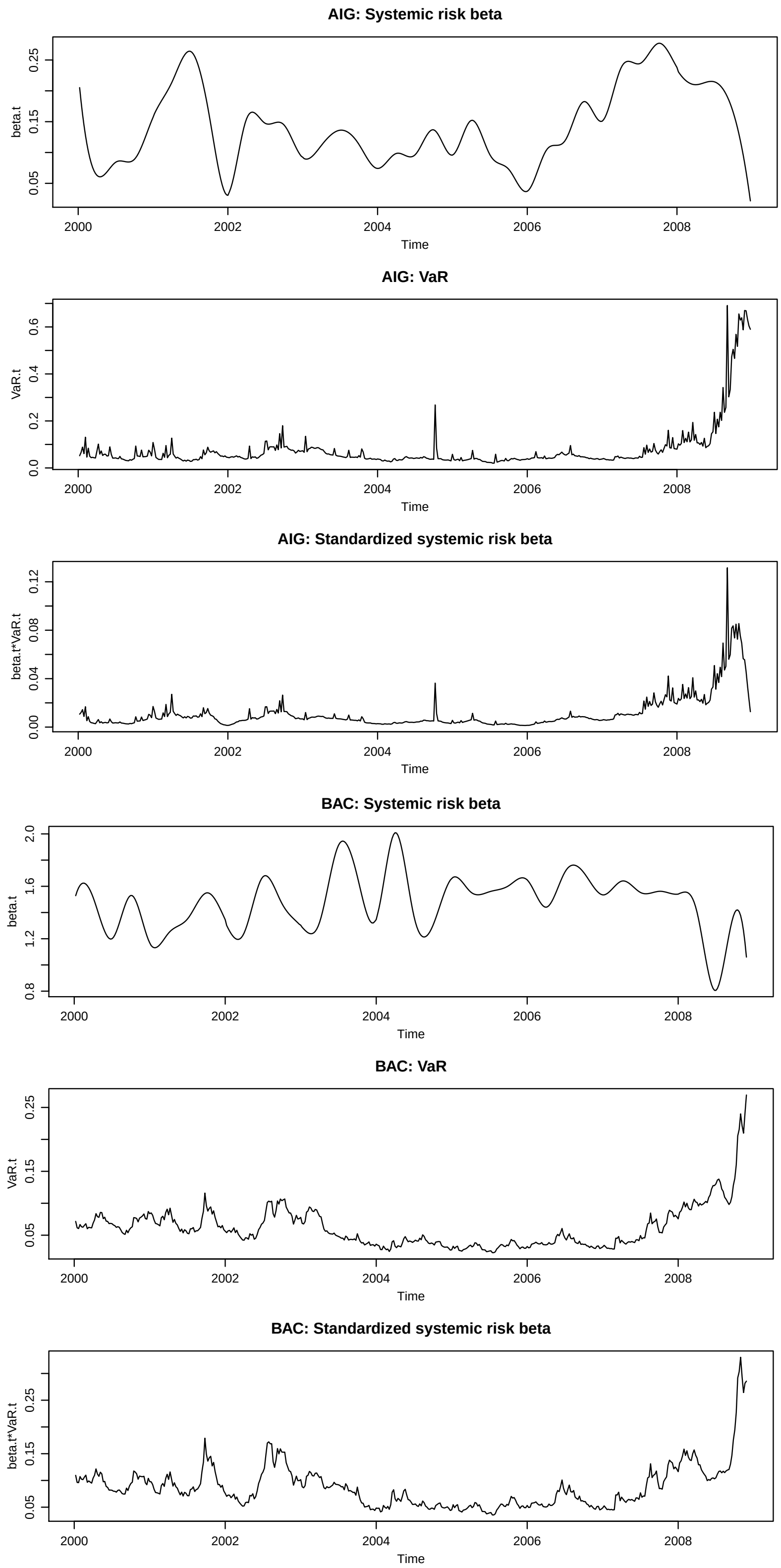

Figure 8: The upper three panels depict time-varying systemic risk beta, time-varying VaR and the product of the two, standardized systemic risk beta, for American International Group (AIG). The lower three panels show the respective three time series for Bank of America (BAC).

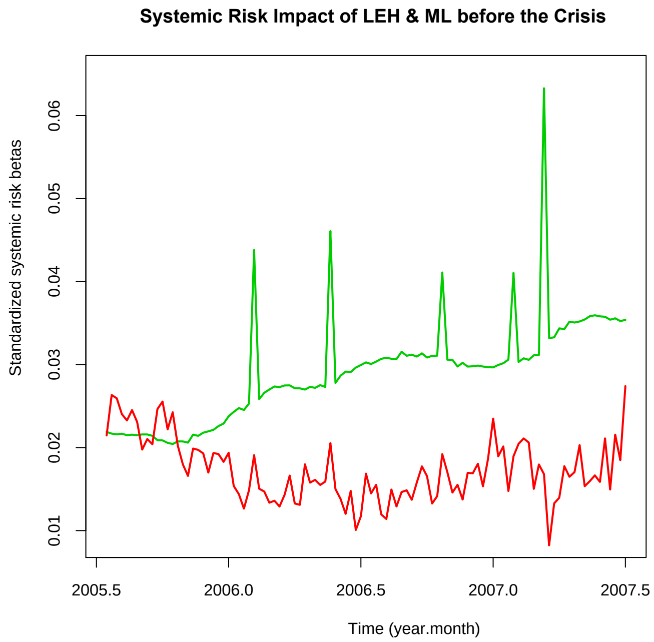

Figure 9: Standardized systemic risk betas, i.e., the products of estimated systemic risk betas and individual VaRs, of Lehman Brothers (LEH, green) and Merrill Lynch (ML, red) during the two years before the financial crisis, mid 2005 - mid 2007. Estimation period is the pre-crisis period, 2000 - mid 2007.

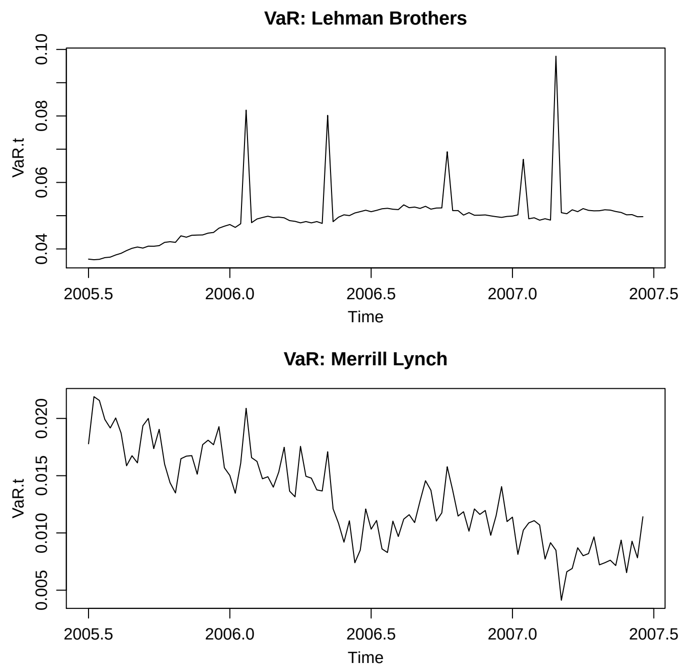

Figure 10: Estimated company-specific VaRs of Lehman Brothers (upper panel) and Merrill Lynch (lower panel) during the two years before the financial crisis, mid 2005 - mid 2007. Estimation period is the pre-crisis period, 2000 - mid 2007.

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