Financial Network Systemic Risk Contributions

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April 10, 2015

Motivation

- The financial crisis showed that thinking about individual risks was not enough. We needed to think about the relationship between them.
- Current financial regulation is micro in nature focusing upon individual risk.
  - Basel II is focused upon VaR.
- To make regulations governing systemic risk, we have to measure it and identify the "too-connected-to-fail" institutions.
- Most of network literature has been focused on average connectedness, but from a systemic risk perspective what we care about is how connected firms are in bad times.

Identifying Relevant Tail Risk Measures

- What we actually care about is the relationship between financial institutions in the tail.
- VaR is the most common measure of tail risk.
- $Pr(-X_t^i \geq VaR_{q,t}^i | W_t^{(i)}) = q$. That is $VaR_{q,t}^i) W_t^{(i)})$ is the q-th negative conditional quantile of returns.
- CoVaR (Conditional Value-at-Risk) measures the VaR of the financial system conditional on the firm i being in distress.

Realized Systemic Risk Beta

- We identify the relevant tail risk drivers as the minimal set of macroeconomic fundamentals, firm-specific characteristic and risk spillovers from other firms using a VaR approach.
- This gives a reliable measure of a firm's idiosyncratic risk in the presence of network effects.
- A company's contribution to systemic risk is then defined as the effect of an increase in its individual tail risk on the VaR of the entire system.

Methodology

- General framework is two-stage quantile regression.
- In the first step, firm-specific VaRs are estimated as functions of firm characteristics, macroeconomic state variables, and tail risk spillovers of other banks captured as loss exceedances.
- We reduce the high-dimensional set of possible cross-linkages between all firms to a feasible number use a LASSO technique developed by Belloni and Chernozhukov 2011 to select the relevant tail risk drivers for each company.

Methodology

- In the second step we measure a firm's systemic impact by individually estimating the VaR of the value-weighted index of the financial sector as a function of the firms' estimated VaR, controlling for the pre-identified company-specific risk drivers and macroeconomic state variables.
- We also develop a novel bootstrap procedure that takes into account the estimation errors from the first step to develop accurate standard errors.

Systemic Risk Beta

- We say a firm is systemically relevant if the marginal effect of its VaR on the VaR of the entire system is statically significant and non-negative.
- We call this the marginal effect systemic risk beta.
- We model his a function of firm-specific characteristics.
- The "realized" systemic risk beta is the product of this and the firm's VaR.
- We use this to rank the systemic importance of various firms.

Determining Drivers of Firm-Specific Tail Risk

- Estimate a conditional VaR.
- We consider a large set of potential regressors $\mathbf{W}_t$ containing lagged macroeconomic state variables, lagged firm-specific characteristics, the firm-specific lagged return, and influences of other companies, which are captured in term of so-called loss exceedances.
- A Loss exceedance is defined for firm j as $E_t^j = X_t^j I(X_t^j \leq \hat{Q}_{0.1})$, where $\hat{Q}_{0.1}$ is the unconditional 10% sample VaR of company j's return X^j. Note: An expected shortfall is just the expectation of the loss exceedance.
- We model the conditional VaR as a linear function of the selected regressors which once we have selected the relevant tail-risk drivers can be estimated from standard linear quantile regression.

Selecting the Tail-Risk Drivers

- We select these in a data-driven way by employing the LASSO.
- The LASSO has recently been adapted to quantile regression by Belloni and Chernozhukov (2011).
- We run the lasso to select the model, and then rerun the quantile regression to get finite-sample unbiased estimates of the effects.
- When we rerun the quantile estimation procedure we drop a regressor if the absolute value of its estimated effect fell below $\tau = 0.0001$.
- For each institution, we choose the lasso weight λ^i in a completely data-driven way by using the supremum norm of a rescaled gradient of the sample criterion function evaluated at the true parameter value as in Belloni and Chernozhukov (2011).

Evaluating the Goodness of Fit

- We consider the VaR specification as inadequate if it fails to produce the correct empirical level of VaR exceedances or if the sequence of exceedances is not i.i.d.
- This ensures that the VaR violations today do not contain information about VaR violations in the future and that both occur according to the same distribution.
- This is tested using a likelihood ratio version of the dynamic quantile test developed by Engle and Manganellli (2004).

VaR Specifications

- We estimate the VaR for the quantile q $= 5\%$.
- The dominant drivers of company-specific VaRs are loss exceedances of other firms.
- In their presence, macroeconomic variables and firm-specific characteristics are often not statistically significant and are not selected by the LASSO procedure.
- This procedure also allows us to assign directions to the "relevant" risk connections.

Tail Risk Network

- If E^j is LASSO selected in the VaR estimation for from i, then we let the coefficient in the quantile post-lasso regression marks the impact of firm j on firm i in the network.
- This gives a weighted, directional network effect between the two firms.

Data: Individual Returns

We focus on fifty-seven financial institutions that exited throughout the period from the beginning of 2000 to the end of 2008, giving 467 weekly observations.

- One big problem with estimating financial networks is that data on connections between firms' assets and obligations are largely proprietary and far from comprehensive.
- We use publicly accessible market and balance sheet data.
- Daily equity prices are obtained from Datastream and converted to weekly log returns.

Data: Macroeconomic Variables

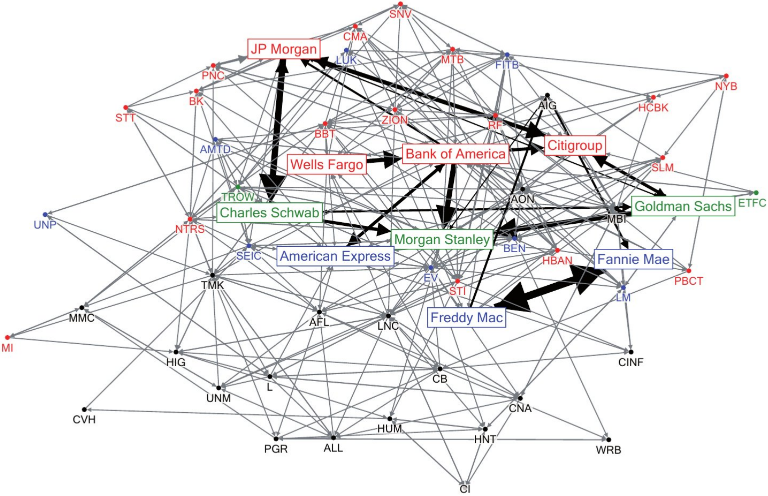
We also used weekly observations of seven lagged macroeconomic variables as in Adrian and Brunnermeier (2011).

- Implied Volatility Index (VIX).
- A short-term "liquidity spread" computed as the difference of the 3-month collateral repo rate and the 3-month Treasury bill rate.
- The change in the 3-month Treasury bill rate.
- The change in the slope of the yield curve.
- Credit spreads between BAA rated bonds and the Treasury bill rate at 10-year maturity.
- The weekly equity market return from CRSP.
- 1-year cumulative real estate sector return from CRSP.

Data: Characteristics of Individual Firms

- Leverage (calculated as the value of total assets divided by total equity.
- Maturity mismatch (calculated as short-term debt net of cash divided by total liabilities.
- Market-to-book value.
- Market capitalization.
- Equity return volatility computed from daily equity return.
- 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.

Risk Network of the US Financial System



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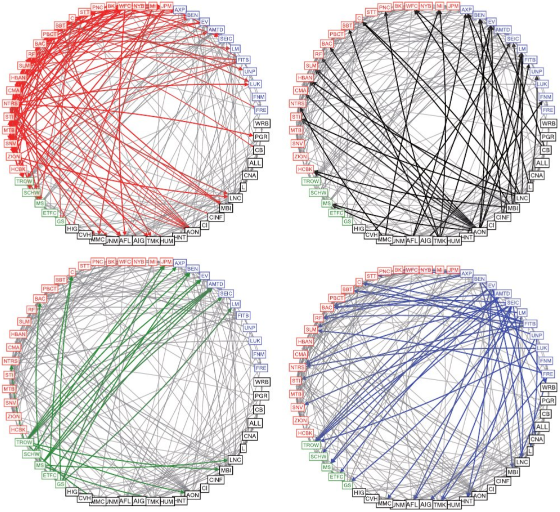


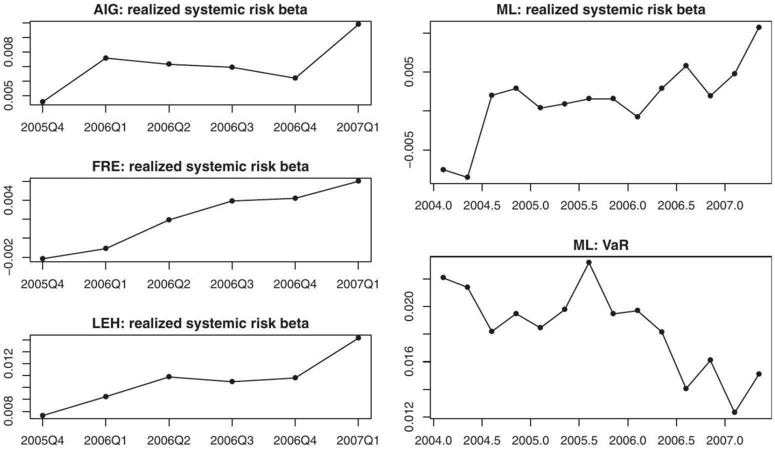
Systemic Risk Beta

- We define the systemic risk beta $\beta_{p,q}^{s|i}$ as marginal effect of firm i's VaR on the system VaR.
- It can be interpreted by analogy with an inverse asset pricing relationship in quantiles where firm i's $q-th$ return quantile drives the $p-th$ quantile of system.

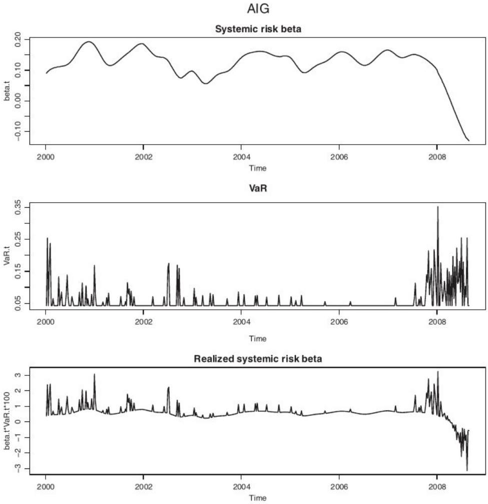
Estimation of Risk Betas

- We allow the betas to be time-varying by assuming they follow a linear model in lagged observable factors.
- We again use the two-step quantile lasso procedure as described above.
- This two-step procedure renders typical bootstrap standard errors unusable.
- Therefore, they provide a results for how to do correctly do boostrap estimation.
- They also detail a formal statistical procedure to test for a firm's statistical relevance, including the proper boostrap procedure of the adjusted "wild-type" method.

Realized System Risk Betas



Systemic Risk Betas



Comments

- Very good paper. Trying to estimate a tail-risk network is extremely important for macroprudential policy issues.
- Using LASSO to select connections seems highly reasonable. To get good network estimates in high-dimensional system, you have to restrict some of the connections to zero in a data-driven way.
- Why not just use quantile regression with a lasso penalty and keep the same coefficients. It should reduce estimation complexity and likely give you better results in a mean square error sort of sense.
- They show that their realized risk measure for AIG would have predicted the financial issues pre-2008, but this is entirely driven by the VaR.

Comments

- They do not even try to connect what they are doing to the structural networks literature, saying it is too difficult.
- A good understanding of systemic risk certainly includes both. Can you write down a theoretical model with quantitative implications for the relationship between banks VaRs?
- The main drivers of the VaR's of firm i are the loss exceedances of firm j, but these are closely related concepts. One should not assume that the relationship is weak enough to just be ignored as they do.