Forecasting systemic impact in financial networks

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Network-based systemic risk assessment

- Theory (Hellwig, 2009): “Regulatory reform must [...] address the risks generated by [...] interdependence and by the lack of transparency about systemic risk exposure.”

- Empirics (HSS, 2012): Systemic relevance of a firm is even mainly determined by network interdependences in tail risks.

- Regulation (Basel III, 2013): “SIFIs must have higher loss absorbency capacity to reflect the greater risks that they pose to the financial system.”
Network-based systemic risk assessment

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- Need effective forecasts of a transparent measure for systemic risk that takes interdependence (risk spillovers) into account.
We take a parsimonious Econometric approach (HSS 2012)

- Systemic impact of an individual company quantified as realized systemic risk beta, the total effect of a company’s VaR on the VaR of the entire system

- **Network-augmented** measure of systemic risk based entirely on publicly available data: individual firms’ risk determined from other companies tail risk and individual and market characteristics, “relevant” (network)-components selected in a data-driven way
Contribution of this paper

- Completely data-driven determination of time-varying tail risk networks capturing potential changes in network structures.
- Rolling window estimation of systemic risk betas (1 year), updated each quarter for flexible up-to-date predictions.
Further literature on empirical systemic risk measurement

- Tail dependence in returns:
  - “CoVaR”: Adrian/Brunnermeier, 2011
  - “VAR for VaR”: White/Kim/Manganelli, 2012


Outline

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2. Methodology
   ▶ Time-varying Networks
   ▶ Forecasting systemic risk betas
3. Empirical Results
4. Conclusion
Measuring systemic risk

“Stress test scenario”: Given the information today, what is the total predicted increase of the financial system’s Value at Risk ($VaR^s_t$) in the next quarter when some bank $i$ is in distress?

$$VaR^s_t = \alpha^s + \beta_{s|i}^s \cdot VaR^i_t + V_{t}^{(i)'} \gamma,$$

1. $V_{t}^{(i)} = (M_{t-1}', VaR_t^{(-i)'})'$ contains “relevant” control variables
2. $\beta_{s|i}^s = \beta_{s|i}^s \cdot VaR^i_t$ is the so-called “realized systemic risk beta”.

Forecasting systemic impact in financial networks
Measuring systemic risk

“Stress test scenario”: Given the information today, what is the total predicted increase of the financial system’s Value at Risk (\(VaR^s\)) in the next quarter when some bank \(i\) is in distress?

\[
VaR^s_t = \alpha^s + \beta^s|i \cdot VaR^i_t + V^{(i)'}t \gamma,
\]  

\(\beta^s|i \) is the so-called “realized systemic risk beta”.

Challenges:

1. Unknown \(VaR^i\): Determine \(i\)-relevant risk factors constituting networks of tail risk spillovers varying over time. \(\Rightarrow\) Model selection?

2. \(\beta^s|i \) is time-varying marginal effect of a generated regressor in a QR framework. \(\Rightarrow\) Effective forecast \(\hat{\beta}^s|i \) of realized beta?
1. \textit{VaR}^i: Model

In a financial system of \( n \) banks (here: \( n = 20 \)), each bank \( i \)'s VaR in week \( t \) may depend on \( K \) observable risk drivers

\[
R^i_t = (Z^i_{t-1}', M_{t-1}', Ex_t^{-i}')',
\]

with

- individual company characteristics \( Z^i_{t-1} \) (updated quarterly, not interpolated)
- general market conditions \( M_{t-1} \), and
- excess losses of others \( Ex_t^{-i} \), with \( m \)-th entry

\[
Ex_t^m = X_t^m \cdot 1(X_t^m < q_{0.1}(X_t^m)), \ m \neq i.
\]
Data

- Daily returns of 20 financial institutions (largest European banks + 6 insurances, all FSB 2011 relevant) from 2006-2010
- System return: value-weighted index of financial institutions in Europe (FTSE Europe Financials)
- Quarterly balance sheet characteristics $Z_t^i$:
  - Leverage: total assets divided by total equity
  - maturity mismatch: quotient of short-term and total debt
  - size: logarithm of total assets
  - quarterly stock price volatility: estimated between quarterly reports.
- Market externalities $M_t$:
  a) financial indicators:
     - return on EuroStoxx 600,
     - relative changes of the volatility index VStoxx,
     - returns on IBOXX Sovereign, iBOXX Subsovereigns, and iBOXX Corporates
     - changes in three months Euribor
proxy for the risk free rate: liquidity spread of three months Eurepo and three month Bubill
proxies for aggregate credit quality in Europe: changes in one and five year Fitch default probability indices and changes in five year continued series of iTraxx Europe (CDS index).

- gold price
- relative changes of the MSCI Europe Real Estate Price Index.

b) Proxies for market expectations on economic growth, country-specific effects and global interconnectedness:
- ten year government bond yields (D, UK, ES, USA, GR)
- yield spreads (ten years minus three months yields) of German and U.S. government bonds
- returns on financial sector indices, FTSE Financials Japan, Asia, and US.
1. **VaR⁰**: Model Selection

- Model selection via “QR-LASSO” (Belloni/Chernozhukov 2011): Demean $R_i$ and minimize

$$\frac{1}{T} \sum_{t=1}^{T} \rho_p \left( X_t^i - R_t^i \xi \right) + \lambda_i \frac{\sqrt{p(1-p)}}{T} \sum_{k=1}^{K} \hat{\sigma}_k |\xi_k|,$$

over $K$-vector $\xi$, where $\hat{\sigma}_k^2 = \hat{V}[R_{t,k}]$ and $\rho_p(u) = u (p - 1(u < 0))$.

- Data-driven $\lambda^i$-choice via sequential upward procedure: decreasing $\lambda$-grid yields increasing subsets of regressors, test significance with nested F-tests.

- Post-LASSO: Estimation of parameters in a QR with only relevant regressors $R_t^{(i)}$,

$$\hat{\xi} = \arg \min_{\xi} \frac{1}{T} \sum_{t=1}^{T} \rho_p \left( X_t^i - \xi_0 - R_t^{(i)'} \xi^i \right).$$

Forecasting systemic impact in financial networks
1. \textit{VaR}^i: Estimation and time-varying networks

- Estimated \textit{VaR}^i time series corresponds to fitted values:
  \[ -\hat{\text{VaR}}^i_t = \hat{\xi}^i_0 + \hat{\xi}^i R_t(i) \]

- Gather information on “relevant” individual risk drivers in network graphics

- Adequate short-run predictions should only be based on “current” dependency structure which might change with quarterly updated balance sheet information.

- Use one year rolling windows for estimation. Update estimation and networks every quarter \( \tau = 1, \ldots, 16 \)
  \( \Rightarrow \tau \)-specific selection of tail risk drivers \( R_t(i,t) \) and corresponding time-varying tail risk networks.

Forecasting systemic impact in financial networks
European network of tail risk spillovers


Forecasting systemic impact in financial networks
2. Forecasting Systemic Impact

- Determine the realized beta from

\[ \text{VaR}_t^s = \alpha^{s,t} + \beta^{s|i,t}(Z_{t-1}^{i*}) \text{VaR}_t^i + \gamma^{s,t} M_{t-1} + \theta^{s,t} \hat{\text{VaR}}_t^{(-i,t)} , \]

via standard quantile regression, where \( \hat{\text{VaR}}^{(-i,t)} \) comprises tail risks of all other banks in the system selected as relevant risk drivers for bank \( i \) at time \( t \).

- The marginal \( \beta^{s|i,t} \) might vary linearly over time in selected firm-specific balance sheet characteristics \( Z_{t-1}^{i*} \).

- Determine parameters at the beginning of each quarter, based on observations dating back no longer than one year.
Predict the systemic relevance of a company from the beginning of the $l$-th quarter $t_l$ to the next quarter $t_{l+1}$ as realized beta

$$\tilde{\beta}^{s|i}_{t_{l+1}|t_l} = \hat{\beta}^{s|i,t_l}(Z^{i*}_{t_l-1}) \hat{VaR}_{t_l}^i$$

where $t_l$ denotes information up to time $t_l$ and $l = 1, \ldots, \tau$.

Within a quarter $l$, predictions are updated by

$$\tilde{\beta}^{s|i}_{t+1|t} = \hat{\beta}^{s|i,t_l}(Z^{i*}_{t_l-1}) \hat{VaR}_{t}^i$$

for any time point $t_l \leq t < t_{l+1}$.
Empirical Results for Europe

Time-varying European tail risk networks


Forecasting systemic impact in financial networks
Systemic risk contributions in Europe

Forecasting systemic impact in financial networks
“Traffic light system” for systemic relevance

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categories according to realized systemic risk beta $\tilde{\beta}^{s|i}$ at the respective end-of-quarter:

'high': $\tilde{\beta}^{s|i}$ above the 75% quantile of all realized systemic risk betas,
'low': $\tilde{\beta}^{s|i}$ below the respective 25% quantile,
'medium': all others

Forecasting systemic impact in financial networks
Out-of-sample forecast evaluation

► Use quarterly tail correlations between the system and each individual company’s return as benchmark for the ex-post unobservable “true” systemic risk contribution:

$$\hat{\rho}^{s,i}_l = \text{corr} (X^s_t, X^i_t | X^s_t < q_{0.1}(X^s_t), X^i_t < q_{0.1}(X^i_t), t \text{ in quarter } l)$$

► Evaluate the performance of the systemic risk beta forecast by the $R^2$ in the forecast regression

$$\hat{\rho}^{s,i}_l = \gamma_0 + \gamma_1 \hat{\beta}^s_{l|l-1} + \varepsilon^{s,i}_l$$

where $l$ is the quarter index. Compare to the performance of simple CAPM-$\beta$ forecasts based on the same estimation period.
Boxplots of $R^2$ from forecast regressions

Forecasting systemic impact in financial networks
The drivers of systemic risk beta $\tilde{\beta}^s|i$

Main finding

The main determinants of realized systemic risk betas are network spillovers - the influence of balance sheet characteristics decreases during the crisis

- Compare rankings according to quarterly averages of $\tilde{\beta}^s|i$ to rankings according to size, leverage, and maturity mismatch via rank correlations (Kendall’s $\hat{\tau}$)

| firm characteristic | $\hat{\tau}$-rank correlation with $\tilde{\beta}^s|i$ for pooled data |
|---------------------|---------------------------------------------------------------|
| size                | 0.07**           | -               |
| leverage            | 0.11***          | -               |
| maturity mismatch   | 0.11***          | -               |

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

Forecasting systemic impact in financial networks
Conclusion

- Framework for forecasting financial institutions’ marginal contribution to systemic risk based on their interconnectedness in terms of extreme downside risks.

- Rolling window out-of-sample prediction setting based on time-varying networks (balance between forecasting stability and responsiveness).

- Qualitative (tail risk network) and quantitative (systemic risk ranking) tool for a timely market surveillance via continuous assessment of systemic risk dependencies based on market data.

- Detect dynamic nature of interconnectedness and corresponding risk channels in the European financial system.
Algorithm for determining risk-drivers

**Step 1**: For each $c \in \Delta_c$, determine the penalty parameter $\lambda_{t_0}^i(c)$ from the data in the following two sub-steps as in BC 2011:

**Step a)** Take $\tau + 1$ iid draws from $U[0, 1]$ independent of $R_{t_0-t}, \ldots, R_{t_0}$ denoted as $U_0, \ldots, U_{\tau}$. Conditional on observations of $R$, calculate

$$\Lambda_{t_0}^i = (\tau + 1) \max_{1 \leq k \leq K} \frac{1}{\tau + 1} \left| \sum_{t=0}^{\tau} \frac{R_{t_0-t,k}(q - I(U_t \leq q))}{\hat{\sigma}_k \sqrt{q(1-q)}} \right| .$$

**Step b)** Repeat step a) $B=500$ times generating the empirical distribution of $\Lambda_{t_0}^i$ conditional on $R$ through $\Lambda_{t_01}^i, \ldots, \Lambda_{t_0B}^i$. For a confidence level $\alpha = 0.1$ in the selection, set

$$\lambda_{t_0}^i(c) = c \cdot Q(\Lambda_{t_0}^i, 1 - \alpha | R_{t_0-t}),$$

where $Q(\Lambda_{t_0}^i, 1 - \alpha | R_{t_0-t})$ denotes the $(1 - \alpha)$-quantile of $\Lambda_{t_0}^i$ given $R_{t_0-t}$.
Step 2: Run separate $l_1$-penalized quantile regressions for $\lambda_{t_0}^i(c_1)$ and $\lambda_{t_0}^i(c_2)$ from step 1 and obtain

$$
\tilde{\xi}_{q_{t_0}}^i(c) = \arg\min_{\xi^i} \frac{1}{\tau + 1} \sum_{t=0}^{\tau} \rho_q \left( X_{t_0-t}^i + R'_{t_0-t} \xi^i \right) + \lambda_{t_0}^i(c) \frac{\sqrt{q(1-q)}}{\tau} \sum_{k=1}^{K} \hat{\sigma}_k |\xi_k^i|,
$$

with the set of potentially relevant regressors $R_{t_0-t} = (R_{t_0-t,k})_{k=1}^{K}$, componentwise variation $\hat{\sigma}_k^2 = \frac{1}{\tau + 1} \sum_{t=0}^{\tau} (R_{t_0-t,k})^2$ and loss function $\rho_q(u) = u(q - I(u < 0))$, where the indicator $I(\cdot)$ is 1 for $u < 0$ and zero otherwise.
Step 3: Drop all components in $R$ with absolute marginal effects $|\tilde{\xi}_{i,t_0}^j(c)|$ below a threshold $\tau = 0.0001$ keeping only the $K^{i,t_0}(c)$ remaining relevant regressors $R^{(i,t_0)}(c)$ for $c \in \{c_1, c_2\}$. As $c_1 > c_2$, the sets of selected relevant regressors are nested $R^{(i,t_0)}(c_1) \subseteq R^{(i,t_0)}(c_2) = \{R^{(i,t_0)}(c_1), R^{(i,t_0)}(c_2 \setminus c_1)\}$. If $R^{(i,t_0)}(c_2 \setminus c_1)$ is the empty set, restart Step 2 with $\lambda^i(c_2)$ and $\lambda^i(c_3)$ from Step 1. Otherwise re-estimate (2) without penalty term for the larger model $c_2$ only with the respective selected relevant uncentered regressors $R^{(i,t_0)}(c_2)$ and an intercept. This regression yields the post-LASSO estimates $\hat{\xi}^{i,t_0}(c_2)$. Apply an F-test for joint significance of regressors $R^{(i,t_0)}(c_2 \setminus c_1)$ at 5% level. If they are significant, restart Step 2 with $\lambda^i(c_2)$ and $\lambda^i(c_3)$ from Step 1b. Continue until additional regressors $R^{(i,t_0)}(c_{l+1} \setminus c_l)$ from penalty $c_l$ to $c_{l+1}$ are no longer found to be significant. Then the final model is obtained from $c_l$ yielding the set of relevant regressors $R^{(i,t_0)}(c_2)$ with corresponding post-LASSO estimates $\hat{\xi}^{i,t_0}(c_l)$ for the coefficients.