Forecasting systemic impact in financial networks

Nikolaus Hautsch
University of Vienna
Julia Schaumburg
VU University Amsterdam
Melanie Schienle
Leibniz University Hannover

Leibniz Universität Hannover

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."

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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

- Out-of-sample forecasting of systemic relevance: tailored methods for prediction of realized systemic risk betas.
- 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.
- Out-of sample forecast study for the European financial market: tail risk networks and systemic risk rankings for years 2006-2010

Further literature on empirical systemic risk measurement

- Tail dependence in returns:
  - "CoVaR": Adrian/Brunnermeier, 2011
  - "Marginal expected shortfall": Brownlees/Engle (2012), Acharaya et al. (2010), Engle/Jondeau/Rockinger (2012)
  - "VAR for VaR": White/Kim/Manganelli, 2012
- Network models: Allen/Gale (2000), Boss et al (2004), Cocco et al (2009), Elsinger et al (2006), Leitner (2005)
- Interbank contagion: Degryse et al (2007), Freixas et al (2000), Furfine et al (2000), Iyer et al (2011), Upper/Worms (2004)
- Default probabilities: Giesecke/Kim (2011), Koopman/Lucas/Schwaab (2011/2012), Huang/Zhou/Zhu (2010)

Outline

1. Introduction
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) in the next quarter when some bank i is in distress?

$$VaR_t^s = \alpha^s + \beta_t^{s|i} \cdot VaR_t^i + \mathbf{V}_t^{(i)'}\gamma, \tag{1}$$

- $\mathbf{V}_t^{(i)} = (\mathbf{M}_{t-1}', \mathbf{VaR}_t^{(-i')})'$ contains "relevant" control variables
- $\overline{\beta}_t^{s|i} = \beta_t^{s|i} \cdot VaR_t^i$ is the so-called "realized systemic risk beta".

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Challenges:

1. Unknown VaR^i: Determine i-relevant risk factors constituting networks of tail risk spillovers varying over time. $\Rightarrow$ Model selection?
2. $\beta_t^{s|i}$ is time-varying marginal effect of a generated regressor in a QR framework. $\Rightarrow$ Effective forecast $\widetilde{\beta}_t^{s|i}$ of realized beta?

1. 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 $\mathbf{R}_t^i = (\mathbf{Z}_{t-1}^{i\prime}, \mathbf{M}_{t-1}^{\prime}, \mathbf{Ex}_t^{-i\prime})^\prime$, with

- individual company characteristics $\mathbf{Z}_{t-1}^i$ (updated quarterly, not interpolated)
- general market conditions $\mathbf{M}_{t-1}$, and
- excess losses of others $\mathbf{Ex}_t^{-i}$, with m-th entry $Ex_t^m = X_t^m \cdot \mathbf{1}\left(X_t^m < q_{0.1}(X_t^m)\right)$, $m \neq i$.

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. VaR^i: Model Selection

- Model selection via "QR-LASSO" (Belloni/Chernozhukov 2011): Demean $\mathbf{R}^i$ and minimize

$$\frac{1}{T}\sum_{t=1}^{T}\rho_p\left(X_t^i - \mathbf{R}^{i\prime}{}_t\boldsymbol{\xi}\right) + \lambda^i\frac{\sqrt{p(1-p)}}{T}\sum_{k=1}^{K}\widehat{\sigma}_k|\xi_k|\ ,$$

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

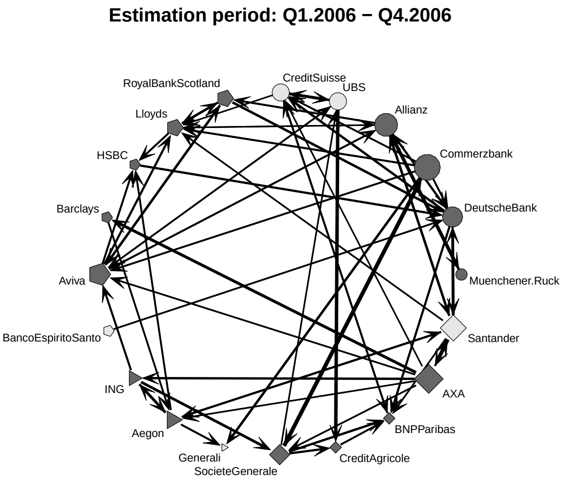
- Data-driven λ^i-choice via sequential upward procedure: decreasing λ-grid yields increasing subsets of regressors, test significance with nested F-tests.
- Post-LASSO: Estimation of parameters in a QR with only relevant regressors $\mathbf{R}_t^{(i)}$,

$$\widehat{\xi} = \arg\min_{\boldsymbol{\xi}^i}\frac{1}{T}\sum_{t=1}^{T}\rho_p\left(X_t^i - \xi_0^i - \mathbf{R}_t^{(i)\prime}\boldsymbol{\xi}^i\right).$$

1. VaR^i: Estimation and time-varying networks

- Estimated VaR^i time series corresponds to fitted values:
$$-\widehat{VaR}_t^i = \widehat{\xi_0^i} + \widehat{\xi^i}\mathbf{R}_t^{(i)}$$
- 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 $\tau = 1, \ldots, 16$
$\Rightarrow$ τ-specific selection of tail risk drivers $\mathbf{R}_t^{(i,t)}$ and corresponding time-varying tail risk networks.

European network of tail risk spillovers



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2. Forecasting Systemic Impact

- Determine the realized beta from

$$VaR_t^s = \alpha^{s,t} + \beta^{s|i,t}(Z_{t-1}^{i*})\widehat{VaR}_t^i + \gamma^{s,t} M_{t-1} + \theta^{s,t}\widehat{VaR}_t^{(-i,t)},$$

  via standard quantile regression, where $\widehat{VaR}^{(-i,t)}$ 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

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

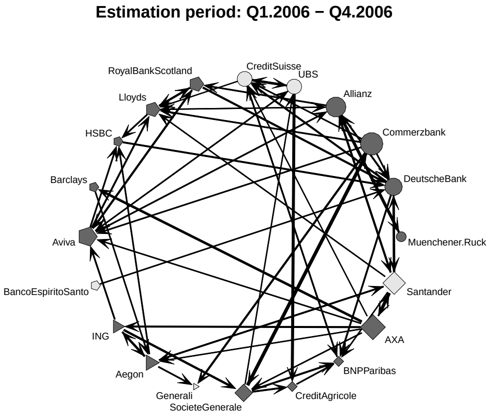
where t_l- denotes information up to time t_l and $l = 1, \ldots, \tau$.

- Within a quarter l, predictions are updated by

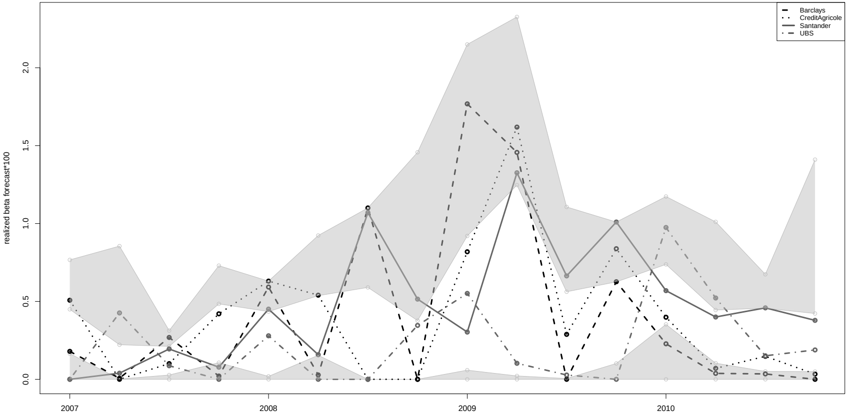
$$\widetilde{\beta}^{s|i}_{t+1|t-} = \widehat{\beta}^{s|i,t_l}(Z^{i*}_{t_l-1})\widehat{VaR}^{i}_{t}$$

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

Time-varying European tail risk networks



Systemic risk contributions in Europe



"Traffic light system" for systemic relevance

	Q2.2007
high	Aviva, BNPParibas, Commerzbank, DeutscheBank, UBS
med.	Aegon, Allianz, AXA, Barclays, CreditSuisse, ING, Munich Re, Santander
low	CreditAgricole, Generali, HSBC, Lloyds, RoyalBankScotland
	Q2.2008
high	Barclays, Commerzbank, CreditAgricole, CreditSuisse, Santander
med.	Aegon, Aviva, BNPParibas, DeutscheBank, Lloyds, Munich Re, RoyalBankScotland, UBS
low	Allianz, AXA, Generali, HSBC, ING
	Q2.2009
high	Aegon, Barclays, CreditAgricole, ING, Santander
med.	Allianz, Aviva, AXA, BNPParibas, HSBC, Lloyds, Munich Re, UBS
low	Commerzbank, CreditSuisse, DeutscheBank, Generali, RoyalBankScotland
	Q2.2010
high	Aviva, CreditSuisse, DeutscheBank, ING, UBS
med.	Aegon, Allianz, AXA, BNPParibas, Generali, HSBC, RoyalBankScotland, Santander
low	Barclays, Commerzbank, CreditAgricole, Lloyds, Munich Re

categories according to realized systemic risk beta $\widetilde{\beta}^{s|i}$ at the respective end-of-quarter:
'high': $\widetilde{\beta}^{s|i}$ above the 75% quantile of all realized systemic risk betas, 'low': $\widetilde{\beta}^{s|i}$ below the respective 25% quantile, 'medium': all others

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:

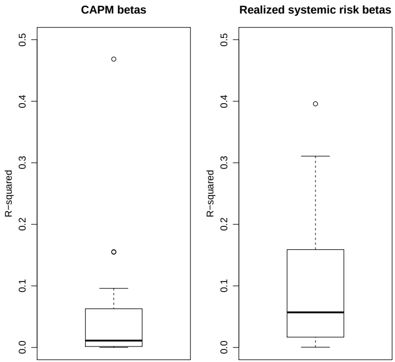
$$\widehat{\overline{\rho}}_l^{s,i} = \widehat{\text{corr}}\left(X_t^s, X_t^i | X_t^s < q_{0.1}(X_t^s), X_t^i < q_{0.1}(X_t^i), t \text{ in quarter } l\right)$$

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

$$\widehat{\overline{\rho}}_l^{s,i} = \gamma_0 + \gamma_1 \widetilde{\beta}_{l|l-1}^{s|i} + \varepsilon_l^{s,i}$$

where l is the quarter index. Compare to the performance of simple CAPM-β forecasts based on the same estimation period.

- Boxplots of R^2 from forecast regressions



The drivers of systemic risk beta $\widetilde{\beta}^{s|i}$

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 $\widetilde{\beta}^{s|i}$ to rankings according to size, leverage, and maturity mismatch via rank correlations (Kendall's $\widehat{\tau}$)
firm characteristic	$\widehat{\tau}$-rank correlation with $\widetilde{\beta}^{s|i}$ for pooled data	
	Q1/2006-Q4/2007	Q1/2008-Q4/2010
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%.

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 $\lambda^i_{t_0}(c)$ from the data in the following two sub-steps as in BC 2011:

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

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

Step b) Repeat step a) B=500 times generating the empirical distribution of $\Lambda^i_{t_0}$ conditional on R through $\Lambda^i_{t_0 1}, \ldots, \Lambda^i_{t_0 B}$. For a confidence level $\alpha = 0.1$ in the selection, set

$$\lambda^i_{t_0}(c) = c \cdot Q(\Lambda^i_{t_0}, 1 - \alpha | R_{t_0-t}),$$

where $Q(\Lambda^i_{t_0}, 1 - \alpha | R_{t_0-t})$ denotes the $(1 - \alpha)$-quantile of $\Lambda^i_{t_0}$ given R_{t_0-t}.

Step 2: Run separate l_1-penalized quantile regressions for $\lambda^i_{t_0}(c_1)$ and $\lambda^i_{t_0}(c_2)$ from step 1 and obtain

$$\widetilde{\xi}_q^{i\,t_0}(c) = \text{argmin}_{\xi^i} \frac{1}{\tau+1} \sum_{t=0}^{\tau} \rho_q \left(X^i_{t_0-t} + R'_{t_0-t}\xi^i \right) + \lambda^i_{t_0}(c) \frac{\sqrt{q(1-q)}}{\tau} \sum_{k=1}^{K} \widehat{\sigma}_k |\xi^i_k| \,, \tag{2}$$

with the set of potentially relevant regressors $R_{t_0-t} = (R_{t_0-t,k})_{k=1}^K$, componentwise variation $\widehat{\sigma}_k^2 = \frac{1}{\tau+1} \sum_{t=0}^{\tau} (R_{t_0-t,k})^2$ 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 $|\widetilde{\xi}^{i}_{t_0}(c)|$ below a threshold $\tau = 0.0001$ keeping only the $K^{it_0}(c)$ 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 $R^{(i,t_0)}(c_1) \subseteq R^{(i,t_0)}(c_2) = \{R^{(i,t_0)}(c_1), R^{(i,t_0)}(c_2 \backslash c_1)\}$. If $R^{(i,t_0)}(c_2 \backslash c_1)$ 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 $\widehat{\xi^{it_0}_q}(c_2)$. Apply an F-test for joint significance of regressors $R^{(i,t_0)}(c_2 \backslash c_1)$ 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 $R^{(i,t_0)}(c_{l+1} \backslash c_l)$ 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 $\widehat{\xi^{it_0}_q}(c_l)$ for the coefficients.