Systemic Risk and Financial Connectedness: Empirical Evidence

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Aix-Marseille School of Economics, June 2024
QFFE 2024 - Quantitative Finance and Financial Econometrics International Conference

Theoretical background

- "Robust-yet-fragile" property of financial system can serve at the same time as shock-absorbers and shock-amplifiers to the financial sector (Haldane 2009).
- This makes the system robust, when the magnitude of shock is relatively small, but fragile, when the shock is large.
- A seminal paper by Acemoglu, Ozdaglar, and Tahbaz-Salehi 2015, provides a formal model, in which an extent of financial contagion exhibits a form of regime transition.
  - When the shocks are small, the damages are dissipated through large number of financial institutions.
  - When the shock is above some threshold, the properties of the system changes markedly. The damages are amplified through the network.

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Research design

- aim is to provide empirical evidence for the regime-dependent effect of connectedness on financial stability, i.e.:
  - Stable markets regime: Higher connectedness → less volatility
  - High shock regime: Higher connectedness → more volatility

- In a following steps:
  - Based on stock prices of the biggest banks in EU and USA, I calculate the connectedness measures in a rolling window basis.
  - This time series measure is then used as an explanatory variable in a Markov switching ARCH model.

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Connectedness measures - denoted κ_t

1. Average correlation: $\frac{\sum_{i \neq i}^{N} \sum_{j \neq j}^{N} \rho_{i,j}(R)}{N^2 - N}$, with $\rho(\cdot)$ being the Ledoit-Wolf estimator of the covariance matrix (Ledoit and Wolf 2003).
2. $\frac{\sum_i^k \lambda_i}{\sum_i^N \lambda_i}$, with λ being an eigenvalue of the covariance matrix.
3. (Granger 1969) - based measure of connectedness:
   - For each of stock pair estimate: $r_{i,t+1} = \beta_0 + \beta_1 r_{m,t} + \beta_2 r_{j,t} + \sum_k^s \beta_{c+2} x_{c,t} + \epsilon_t$
   - The "causality" matrix is set as: $G_{i,j} = \begin{cases} 1 & \text{if } \beta_2 \text{ is significant} \\ 0 & \text{otherwise} \end{cases} \quad \forall i \neq j$
   - As with before we calculate average connectedness: $\frac{\sum_{i \neq j}^{N} \sum_{j \neq i}^{N} G_{i,j}}{N \times (N-1)}$

(Last two measures are as described in Billio et al. 2012)

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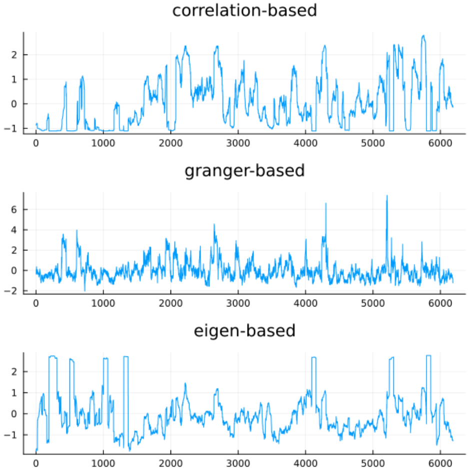
Connectedness measures results

Figure: Standardized time series of connectedness measures for a rolling window of 63 trading days (quarter)



Modeling the regime-dependent effect of connectedness

Mean specification of the model:

$$r_{b,t} = \beta_0 + \underbrace{\beta_1 r_{b,t-1}}_{\text{Banking index}} + \underbrace{\beta_2 r_{m,t-1}}_{\text{Broad market index}} + \epsilon_t$$

The Markov-switching ARCH specification is:

$$\sqrt{\epsilon_t^2} = \alpha_{0,s} + \underbrace{\alpha_{1,s}\kappa_{t-1}}_{\text{connectedness}} + \underbrace{\sum_{i=1}^{p} \alpha_{i+1}\sqrt{\epsilon_{t-i}^2}}_{\text{Lag controls}}$$

With regime changes according to Markov process:

$$P(S_t = i | S_{t-1} = j) = \begin{bmatrix} \pi_1 & 1-\pi_2 \\ 1-\pi_1 & \pi_2 \end{bmatrix}$$

Estimation results

EU banking sector and 252 trading days (year) rolling window

Connectedness measure		Regime 1		Regime 2	
		Estimate	S.E.	Estimate	S.E.
Correlation-based	α_0	0.466*	0.019	1.988*	0.06
	α_1	0.017	0.009	0.22*	0.043
	η	0.435	0.009	1.4	0.012
	$\pi_{i,i}$	78.6%		52%	
Eigenvalue-based	α_0	0.458*	0.018	1.975*	0.061
	α_1	-0.002	0.008	0.052	0.048
	η	0.435	0.009	1.42	0.012
	$\pi_{i,i}$	90%		67.2%	
Granger-based	α_0	0.468*	0.018	1.984*	0.059
	α_1	0.018*	0.008	0.276*	0.05
	η	0.433	0.009	1.394	0.013
	$\pi_{i,i}$	78.5%		52.5%	

* coefficient with 5% statistical significance

US banking sector and 63 trading days (year) rolling window

Connectedness measure		Regime 1		Regime 2	
		Estimate	S.E.	Estimate	S.E.
Correlation-based	α_0	0.402*	0.013	1.517*	0.054
	α_1	0.027*	0.007	0.239*	0.044
	η	0.373	0.007	1.268	0.017
	$\pi_{i,i}$	89.4%		67%	
Eigenvalue-based	α_0	0.416*	0.014	1.554*	0.057
	α_1	0.041*	0.007	0.194*	0.046
	η	0.38	0.006	1.304	0.016
	$\pi_{i,i}$	90%		67.2%	
Granger-based	α_0	0.379*	0.013	1.472*	0.047
	α_1	0.009	0.007	0.205*	0.032
	η	0.356	0.006	1.161	0.013
	$\pi_{i,i}$	87.4%		65%	

* coefficient with 5% statistical significance

Conclusions and future research directions

- The theory is confirmed to some degree - the connectedness effect is indeed regime dependent.
- The effect is assymetric - the connectedness is more important in the high shock regime.
- Further research
  - should control for firm specific balance sheet (preliminarily, the results hold)
  - Possible application of Gaussian graphical models to estimate the connectedness measures

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