# Systemic Risk and Financial Connectedness: Empirical Evidence

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# 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 2015a, 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

- The aim is to provide (and quantify) empirical evidence for the regime-dependent effect of connectedness on financial stability, i.e.:
  - Stable markets regime: Higher connectedness $\rightarrow$ less volatility
  - High shock regime: Higher connectedness $\rightarrow$ 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.
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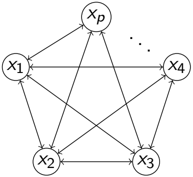
# (Financial) network estimation from time series

$$\underbrace{\begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ x_{31} & x_{32} & \cdots & x_{3n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{T1} & x_{T2} & \cdots & x_{Tn} \end{pmatrix}}_{\text{Time series matrix } \boldsymbol{X} \text{ of size } T \times n.} \xrightarrow{f : \mathbb{R}^{T \times n} \to \mathbb{R}^{n \times n}} \underbrace{\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix}}_{\text{Adjacency matrix } \boldsymbol{A} \times n.}$$

$$||$$




Graph representation of matrix $\boldsymbol{A}$.

# Connectedness measures - denoted $\gamma_t$

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 $\lambda$ 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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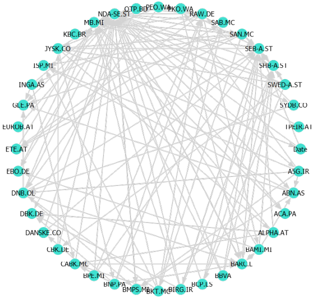
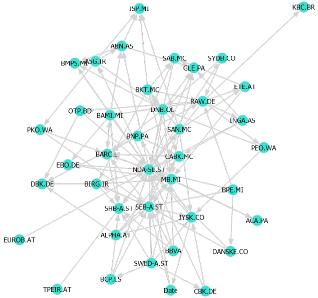
# Example of estimated network



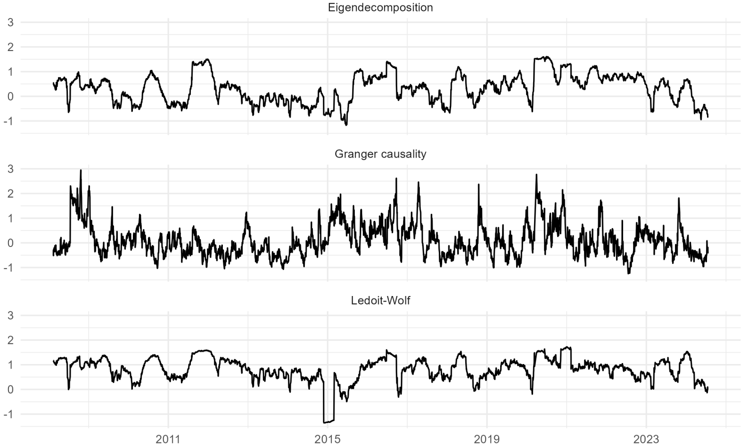

(a) Circle representation of graph




(b) Representation of graph with random position

# Connectedness measures results

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



# Modeling the regime-dependent effect of connectedness

Mean specification of the model:

$$r_{b,t} = \beta_0 + \underbrace{\sum_{i=1}^{k} \beta_i r_{b,t-i}}_{\text{Banking index}} + \underbrace{\sum_{j=0}^{p} \beta_{k+j} r_{m,t-j}}_{\text{Broad market index}} + \epsilon_t$$

The Markov-switching ARCH specification is:

$$\sqrt{\epsilon_t^2} = \alpha_{0,S_t} + \underbrace{\alpha_{1,S_t}\gamma_{t-1}}_{\text{connectedness}} + \underbrace{\sum_{i=1}^{p} \alpha_{i+1}\sqrt{\epsilon_{t-i}^2}}_{\text{lag controls}} + \vartheta_t$$

$$\vartheta \sim \mathcal{N}(0, \eta)$$

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

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

| Connectedness measure | | **Regime 1** | | **Regime 2** | |
|---|---|---|---|---|---|
| | | Estimate | S.E. | Estimate | S.E. |
| Ledoit-Wolf | $\alpha_0$ | 0.37* | 0.013 | 1.342* | 0.037 |
| | $\alpha_1$ | 0.014 | 0.006 | 0.226* | 0.026 |
| | $\eta$ | 0.319 | 0.007 | 0.888 | 0.009 |
| | $\pi_{i,i}$ | 80.64% | | 57.8% | |
| Eigenvalue-based | $\alpha_0$ | 0.378* | 0.014 | 1.337* | 0.037 |
| | $\alpha_1$ | 0.025 | 0.007 | 0.222* | 0.028 |
| | $\eta$ | 0.319 | 0.007 | 0.89 | 0.01 |
| | $\pi_{i,i}$ | 80.3% | | 57% | |
| Granger-based | $\alpha_0$ | 0.375* | 0.013 | 1.352* | 0.036 |
| | $\alpha_1$ | 0.019 | 0.007 | 0.197* | 0.024 |
| | $\eta$ | 0.316 | 0.007 | 0.889 | 0.009 |
| | $\pi_{i,i}$ | 80.7% | | 58.84% | |

* coefficient with 5% statistical significance

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

| Connectedness measure | | **Regime 1** | | **Regime 2** | |
|---|---|---|---|---|---|
| | | Estimate | S.E. | Estimate | S.E. |
| Ledoit-Wolf | $\alpha_0$ | 0.441* | 0.019 | 1.82* | 0.05 |
| | $\alpha_1$ | 0.019* | 0.01 | 0.302* | 0.036 |
| | $\eta$ | 0.401 | 0.009 | 1.209 | 0.011 |
| | $\pi_{i,i}$ | 73.4% | | 48.16% | |
| Eigenvalue-based | $\alpha_0$ | 0.434* | 0.017 | 1.829* | 0.048 |
| | $\alpha_1$ | -0.013* | 0.008 | 0.303* | 0.043 |
| | $\eta$ | 0.49 | 0.008 | 1.22 | 0.11 |
| | $\pi_{i,i}$ | 74.8% | | 60.8% | |
| Granger-based | $\alpha_0$ | 0.445* | 0.018 | 1.824* | 0.05 |
| | $\alpha_1$ | 0.018 | 0.001 | 0.276* | 0.033 |
| | $\eta$ | 0.401 | 0.009 | 1.215 | 0.011 |
| | $\pi_{i,i}$ | 74.56% | | 50.76% | |

* coefficient with 5% statistical significance

# Robustness check - design

- Are there confounders in the bank specific characteristics?
- To check this I use quarterly financial statement data:
    - Data is sourced from Orbis database.
    - Substantial reduction of used data due to lower frequency of reports and their availability.
    - $N$ banks: $51 \rightarrow 30$. $T$ observations $6240 \rightarrow 260$.
    - Quarterly financial data was interpolated (with splines) into weekly data.
    - Financial ratios and financial variable growth was used as a control in the Granger-based connectedness estimation

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# Robustness check - results

Results for EU banks with a rolling window of 52 weeks

| Granger-based | | Regime 1 | | Regime 2 | |
|---|---|---|---|---|---|
| | | Estimate | S.E. | Estimate | S.E. |
| Correlation-based | $\alpha_0$ | 1.524* | 0.19* | 5.031* | 0.53 |
| | $\alpha_1$ | 0.129 | 0.093 | 1.175* | 0.434 |
| | $\eta$ | 1.013 | 0.045 | 2.872 | 0.086 |
| | $\pi_{i,i}$ | 80.36% | | 51.8% | |

* coefficient with 5% statistical significance

# Concluding remarks

- The theory is confirmed to some degree - the connectedness effect is indeed regime dependent.
- The effect is asymmetric - the connectedness is more important in the high shock regime. Consistent with *financial network externality* (Acemoglu, Ozdaglar, and Tahbaz-Salehi 2015b)

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Thank you!

- Contac:t m.dadej@unibs.it
- Working paper and replication code may be found at my github: `github.com/m-dadej/robust_fragile`

# References I


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