Networks and Systemic Instabilities:

from dynamical systems to dynamic network models

"Networks, Spins and Games" IMSc Chennai

Summary

In this talk I will present a series of results on the development of network models and machine learning models for financial stability and systemic risk monitoring:

- Introduction: General stability of dynamical systems on networks
- Core-periphery vs bipartite structure in financial networks
- Network valuation in financial systems
- Common asset holding across financial institutions
- Recognising preferential trading
- Structural edge importance in capital markets transactions
- Hawkes modeling of bursty transaction networks

Introduction:
General stability of dynamical systems on networks

Will a large heterogeneous system on a network be stable?

Criticality in complex systems

A popular conjecture suggests that complex systems have adapted to operate at marginal stability, i.e., near the critical point of the stability transition.

Large fluctuations of the dynamical variables result in power-law distributions of various quantities

Ornstein-Uhlenbeck processes

$$\frac{dx_j}{dt} = -\sum_{j=1}^{N} A_{jk} x_k + \eta_j(t),$$

$$\langle \eta_j(t) \eta_k(t) \rangle = 2D_{jk}\delta_{jk}$$

Krumbeck, Yvonne, et al. "Fluctuation spectra of large random dynamical systems reveal hidden structure in ecological networks." Nature Communications 12.1 (2021): 3625.

Ornstein-Uhlenbeck processes

$$\frac{dx_j}{dt} = -\sum_{j=1}^{N} A_{jk} x_k + \eta_j(t),$$

$$\langle \eta_j(t) \eta_k(t) \rangle = 2D_{jk}\delta_{jk}$$

$$\lambda_{min}(\boldsymbol{A}) > 0$$

Ferreira, Leonardo, Fernando Metz, and Paolo Barucca. "Random matrix ensemble for the covariance matrix of Ornstein-Uhlenbeck processes with heterogeneous temperatures." arXiv preprint arXiv:2409.01262 (2024).

Models of static networks

Fitness model

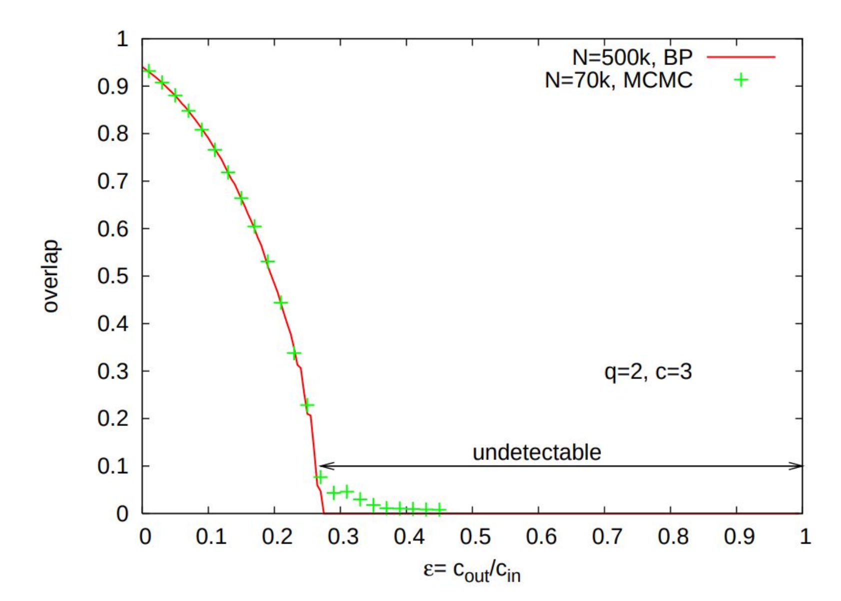
$$\mathbb{P}(\boldsymbol{A}^t|\Theta^t) = \prod_{i,j>i} \mathbb{P}(A^t_{ij}|\theta^t_i, \theta^t_j) = \prod_{i,j>i} \frac{e^{A^t_{ij}(\theta^t_i+\theta^t_j)}}{1+e^{(\theta^t_i+\theta^t_j)}}$$

- No autoregressive model of fitness parameters
- No link copying mechanism
- No memory in the model
- Useless for link prediction without a model for the fitness parameters

Stochastic block model graphs

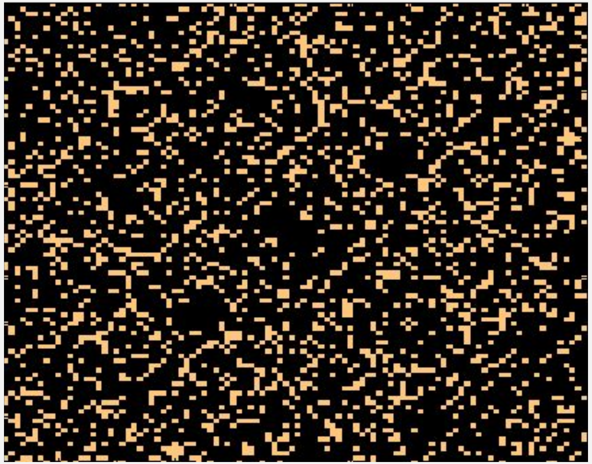
A stochastic block model graph is a random graph where:

- each node is assigned to a block g_i
- each unordered (undirected case) pair of different nodes is randomly linked with probability p_{ab}, where $a=g_i$ and $b=g_j$

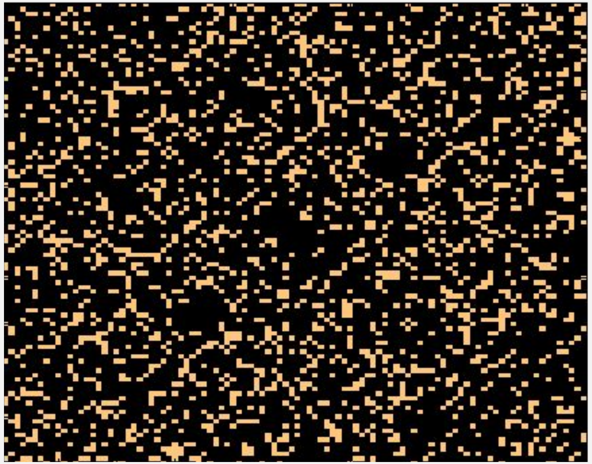


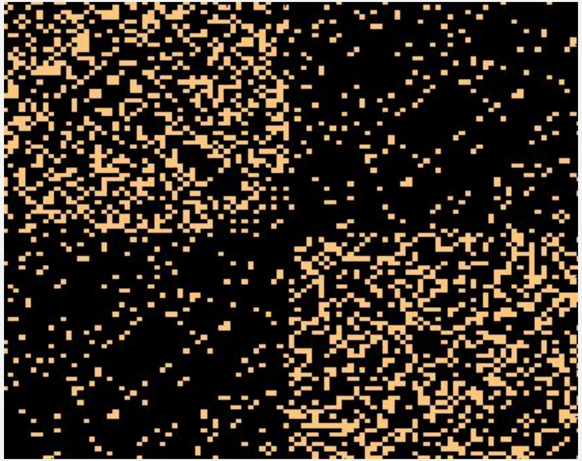
Decelle et al.

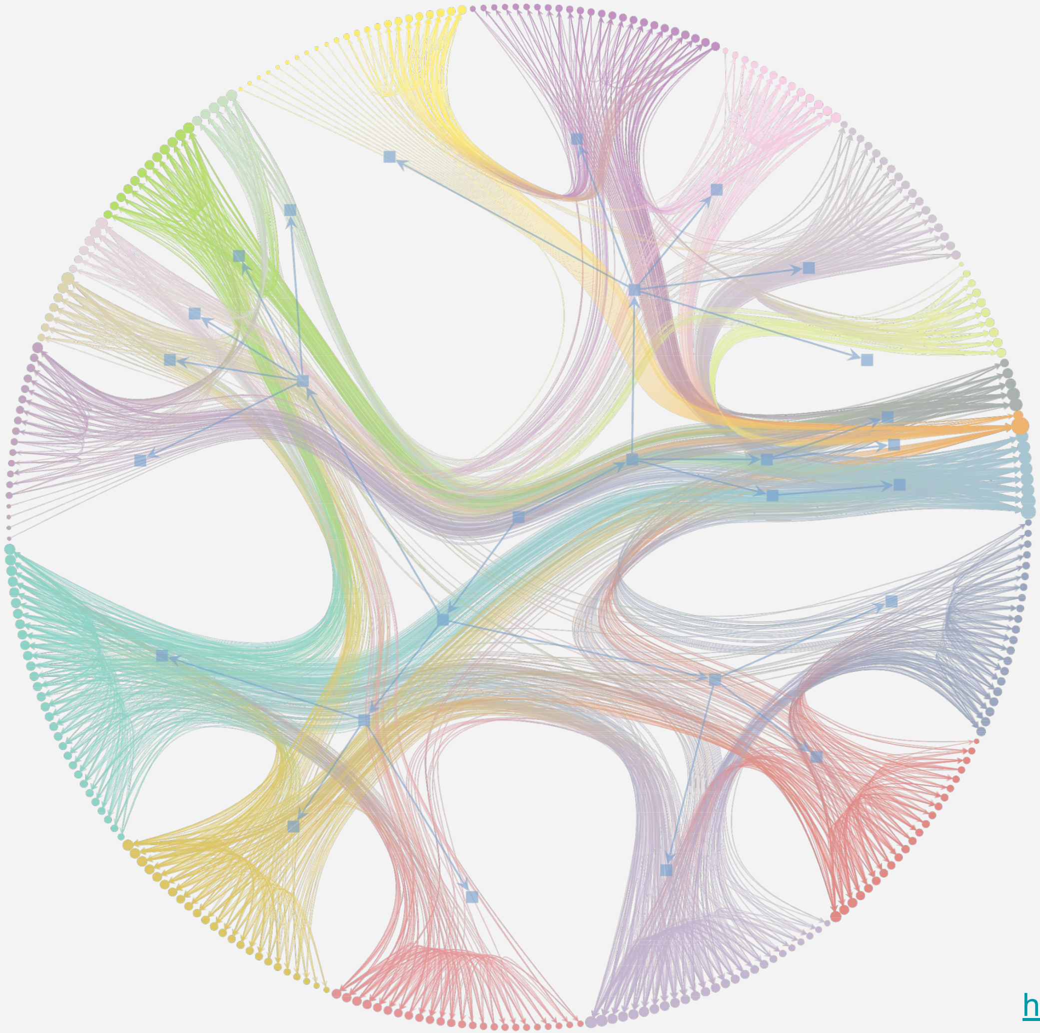
Community detection



Community detection







https://graph-tool.skewed.de/

Identifying core-periphery structure

Research question:

- What is the core of a financial network and how do we find it?

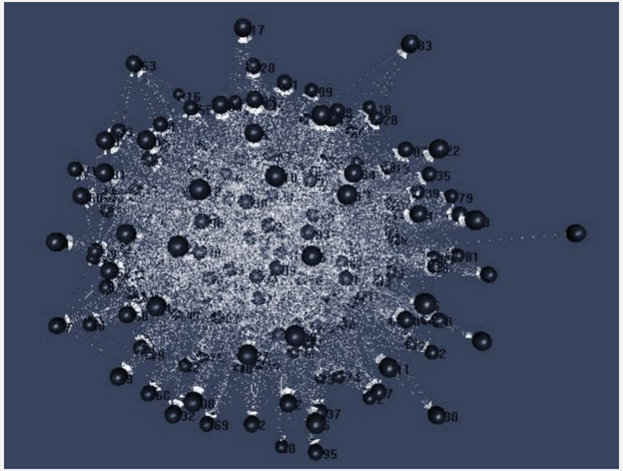


Figure taken from Fricke and Lux (2012)

Relevance and policy implications:

- Risk management for banks in the core and in the periphery can be different
- Network structure affects systemic risk, core banks can be more vulnerable and systemic
- A given position in the structure may correspond to different business strategies
- Capital requirements for core banks can be different

- Fricke, Daniel, Lux, Thomas (2012) : Core-periphery structure in the overnight money market: Evidence from the e-MID trading platform, *Kiel Working Paper*, No. 1759
- Csermely, P., London, A., Wu, L. Y., & Uzzi, B. (2013). Structure and dynamics of core/periphery networks. *Journal of Complex Networks*, *1*(2), 93-123.
- in 't Veld D, van Lelyveld I (2014) Finding the core: network structure in interbank markets. *J Bank Financ* 49:27–40

Beyond McKay's law in equitable graphs

In the core-periphery (k,1,1,0) cavity equations read:

$$\Delta_c^{(c)}(z) = \frac{1}{z - (k-1)\Delta_c^{(c)}(z) - \Delta_p^{(c)}(z)}$$

$$\Delta_c^{(p)}(z) = \frac{1}{z - k\Delta_c^{(c)}(z)}$$

$$\Delta_p^{(c)}(z) = \frac{1}{z}$$

$$\Delta_p^{(p)}(z) = \frac{1}{z - \Delta_c^{(p)}(z)}.$$

Core-periphery (k,1,1,0)-blockmodel graph

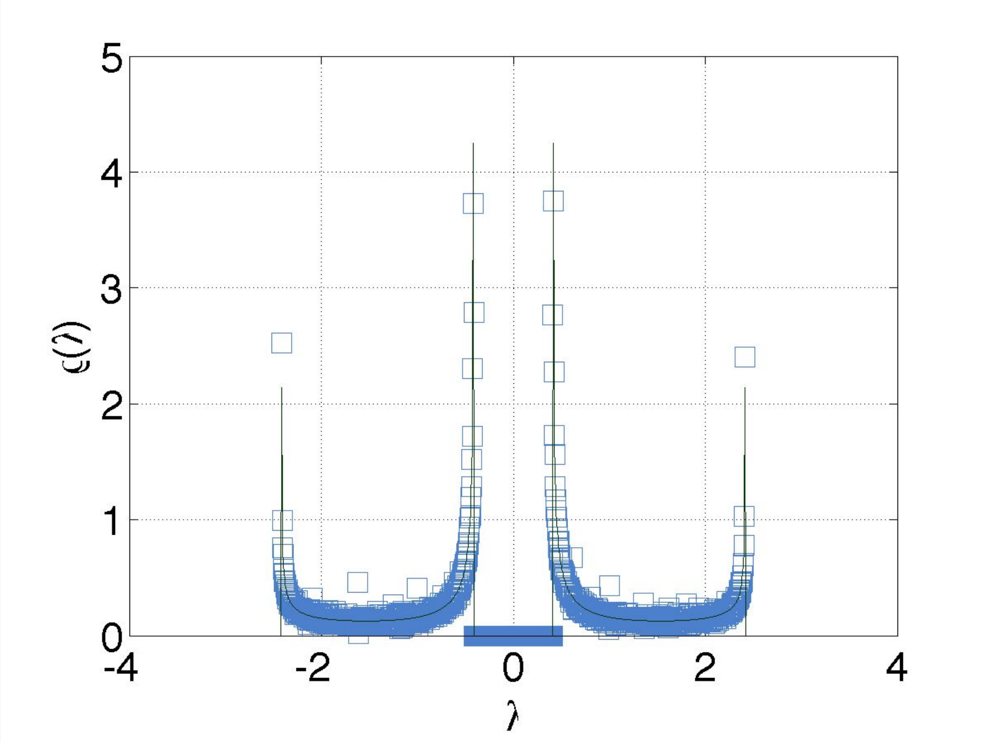
Beyond McKay’s law in equitable graphs

Cavity equations admit a closed-form solution that reads:

$$\rho(\lambda) = \frac{1}{2\pi}\left(\frac{k\beta}{\delta} + \frac{k\beta}{\gamma}\frac{1}{\left(\lambda - \frac{\lambda - k\alpha}{\gamma}\right)^2 + \left(\frac{k\beta}{\gamma}\right)^2}\right)$$

DOE of the core-periphery (k,1,1,0)-blockmodel graph

Beyond McKay's law in equitable graphs



DOE of the core-periphery (2,1,1,0)-blockmodel graph

Identifying strategies in interbank networks

Research question:

- How do we know if there is a core-periphery structure in a complex network, e.g. a network of financial transactions?

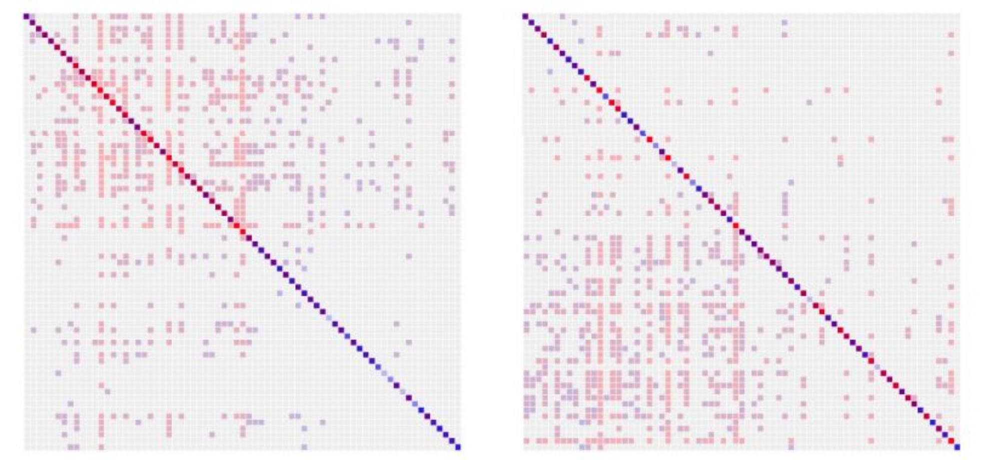


Figure taken from Barucca and Lillo (2016) based on granular eMID data

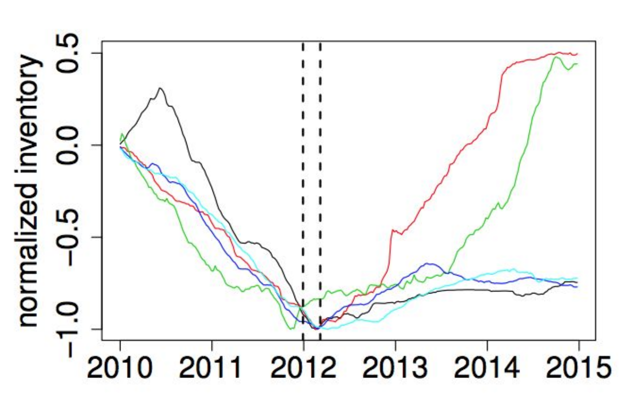
Methodology:

- Stochastic block model generating networks with an arbitrary block structure
- Expectation-Maximization until convergence to the most probable assignment of nodes into groups

Identifying strategies in interbank networks

Main findings:

- Degree heterogeneity can create a (spurious) core-periphery structure
- Time aggregation leads to degree heterogeneity and to the emergence of a core-periphery structure
- eMID mainly displays a *bipartite* structure on a daily and weekly basis with a main division in lenders and borrowers
- Following the ECB LTRO measures the behaviour of banks in the eMID market abruptly changed



References:

- Barucca, P., Lillo, F. (2016). Disentangling bipartite and core-periphery structure in financial networks. *Chaos, Solitons & Fractals*, *88*, 244-253.

- Barucca, P., Lillo, F. (2017). The organization of the interbank network and how ECB unconventional measures affected the e-MID overnight market. *Comput Manag Sci,* 1-22.

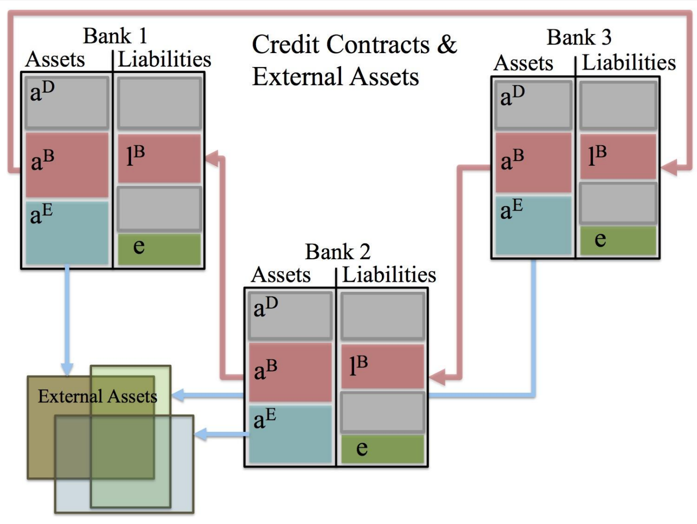
Systemic risk models on static networks

Network valuation in financial systems

Research question:

- What is the value of an interbank asset embedded in a network of liabilities?

Network valuation in financial systems, PB, M. Bardoscia, M. D'Errico, G. Visentin, F. Caccioli, G. Caldarelli, S. Battiston, *Mathematical Finance*



$$\mathrm{d}A_i^e(s) = \mu_i A_i^e(s)\mathrm{d}s + \sigma_i A_i^e(s)\mathrm{d}W_i(s) \qquad \forall s \in [t,T],\ i$$

Network valuation in financial systems

$$E_i(t) = A_i^e(t) - L_i^e(t) + \sum_{j=1}^{n} A_{ij}(t)\mathbb{E}_{\mathbb{Q}}[\mathbb{V}_{ij}^{(\mathrm{EN})}(E_j(T))|\mathcal{F}(t)] - \sum_{j=1}^{n} L_{ij}(t)$$

$$\mathbb{V}_{ij}(E_j(T);\ldots) = \begin{cases} 1 & \text{for } E_j(T) > 0 \\ r_j(E_j(T);\ldots) & \text{for } E_j(T) \leq 0 \end{cases}$$

$$\begin{aligned} p_j^D(E_j(t)) &= 1 - \mathbb{E}_{\mathbb{Q}}\left[\mathbb{1}_{E_j(T)\geq 0}|\mathcal{F}(t)\right] \\ &= \mathbb{E}_{\mathbb{Q}}\left[\mathbb{1}_{E_j(T)<0}|\mathcal{F}(t)\right] \\ &\simeq \mathbb{E}_{\mathbb{Q}}\left[\mathbb{1}_{\Delta A_j^e < -E_j(t)}\middle|A_j^e(t)\right] \end{aligned}$$

$$\begin{aligned} \rho_j(E_j(t)) &= \mathbb{E}_{\mathbb{Q}}\left[\left(\frac{E_j(T)+\bar{p}_j(T)}{\bar{p}_j(T)}\right)^+ \mathbb{1}_{E_j(T)<0}\middle|\mathcal{F}(t)\right] \\ &\simeq \mathbb{E}_{\mathbb{Q}}\left[\left(\frac{E_j(t)+\Delta A_j^e+\bar{p}_j(t)}{\bar{p}_j(t)}\right)\mathbb{1}_{-\bar{p}_j(t)-E_j(t)\leq\Delta A_j^e<-E_j(t)}\middle|A_j^e(t)\right] \end{aligned}$$

The decline of solvency contagion risk

First network valuation study on regulatory data from 2008 to 2016

- Large exposures were collected every quarter from 2008 Q2 to 2013 Q4.

- The second data source covers every quarter in the period from 2014 Q4 to 2016 Q4. It includes exposures between those seven banks across several asset classes: fixed income (unsecured and subordinated debt securities), securities financing transactions (repo, reverse repo, securities lending and borrowing), and derivatives

Bardoscia, Marco, et al. "Forward-looking solvency contagion." *Journal of Economic Dynamics and Control* 108 (2019): 103755.

Bardoscia, Marco, Paolo Barucca, Adam Brinley Codd, and John Hill. "Forward-looking solvency contagion." Journal of Economic Dynamics and Control 108 (2019): 103755.

The decline of solvency contagion risk

Research question:

- How did solvency contagion risk change since the crisis?
- Can we characterize continuously the valuation functions of UK banks?

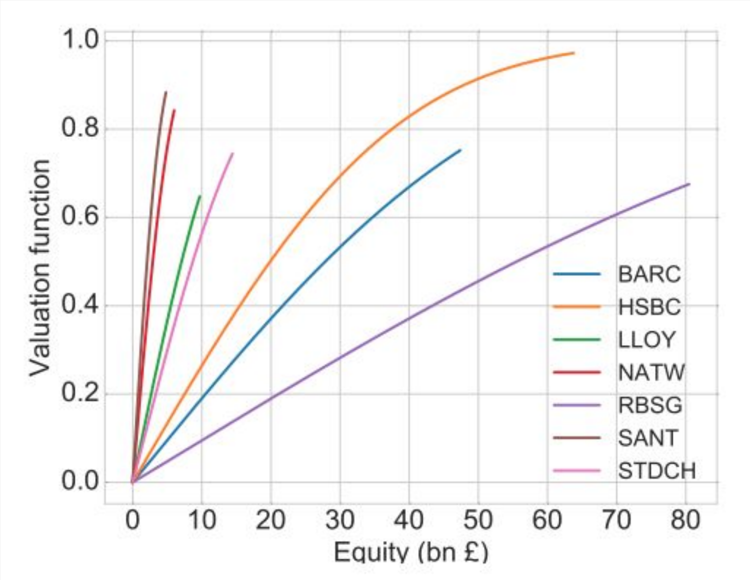
$$\mathbb{V}_{ij}(E_j(T);\ldots) = \begin{cases} 1 & \text{for } E_j(s) > 0,\ \forall s < T \\ r_j(0;\ldots) & \text{otherwise} \end{cases}$$

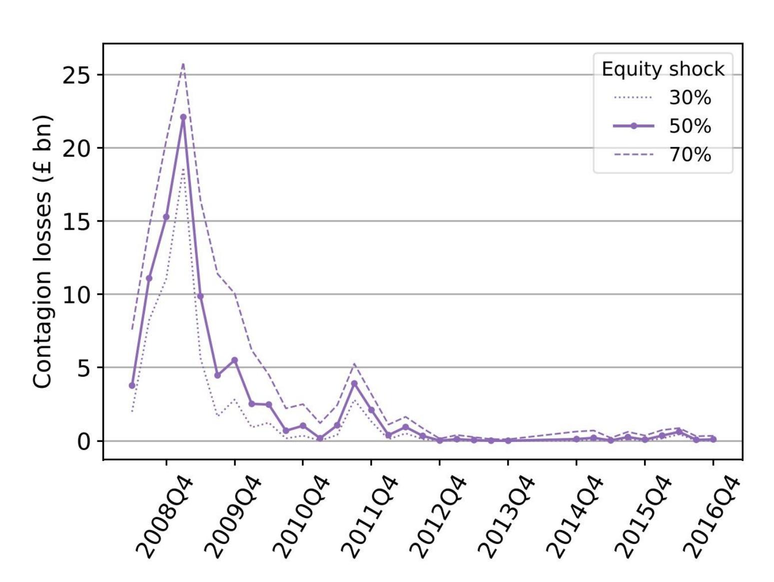
$$\mathbb{E}^{\mathbb{Q}}\left[\mathbb{V}_{ij}(E_j(T);\ldots)|\mathbf{A}^e(t)\right] = 1 - p_j^D(E_j(t)) + \rho\, p_j^D(E_j(t))$$

Bardoscia, Marco, et al. "Forward-looking solvency contagion." *Journal of Economic Dynamics and Control* 108 (2019): 103755.

Bardoscia, Marco, Paolo Barucca, Adam Brinley Codd, and John Hill. "Forward-looking solvency contagion." Journal of Economic Dynamics and Control 108 (2019): 103755.

The decline of solvency contagion risk





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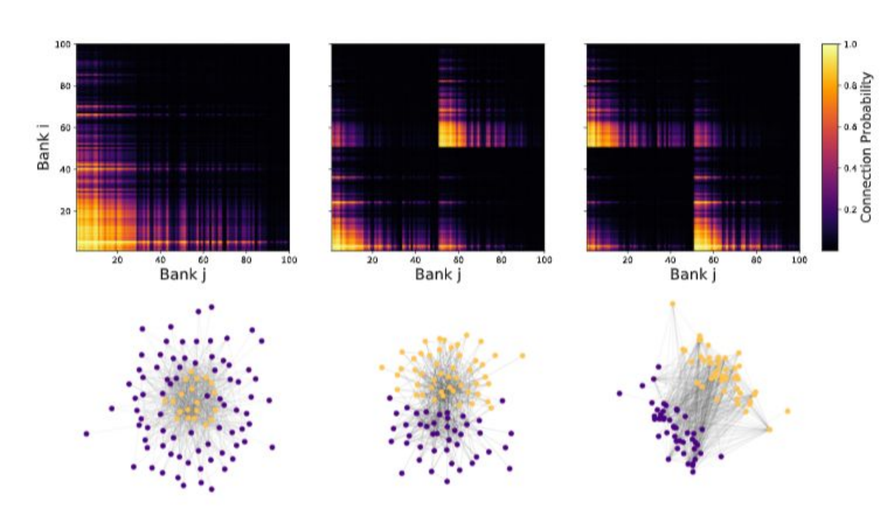
Bardoscia, Marco, Paolo Barucca, Adam Brinley Codd, and John Hill. "Forward-looking solvency contagion." Journal of Economic Dynamics and Control 108 (2019): 103755.

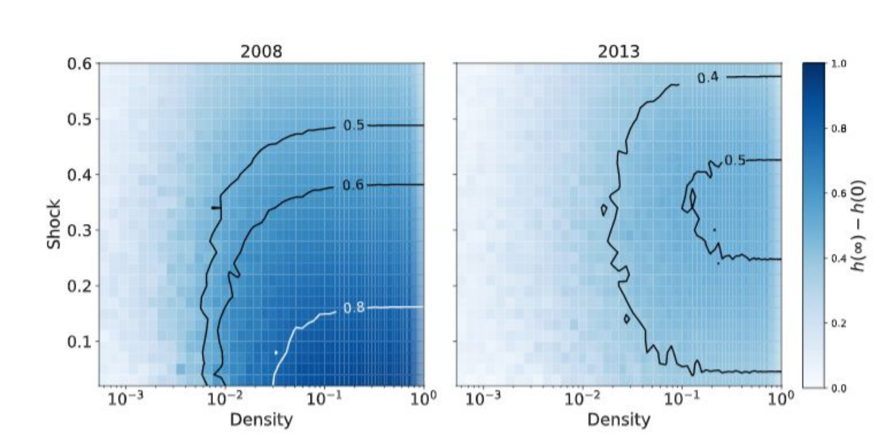
Network sensitivity of systemic risk

Research question:

- How is systemic risk depending on the underlying financial networks?



Ramadiah, Amanah, Domenico Di Gangi, D. Sardo, Valentina Macchiati, Minh Tuan Pham, Francesco Pinotti, Mateusz Wiliński, Paolo Barucca, and Giulio Cimini. "Network sensitivity of systemic risk." *Journal of Network Theory in Finance* 5, no. 3 (2019).



Common asset holding across financial institutions

Research question:

- How similar are the portfolios of asset holding of different types of financial institutions in the UK?
- How could we characterize the vulnerability of institutions based on such information?

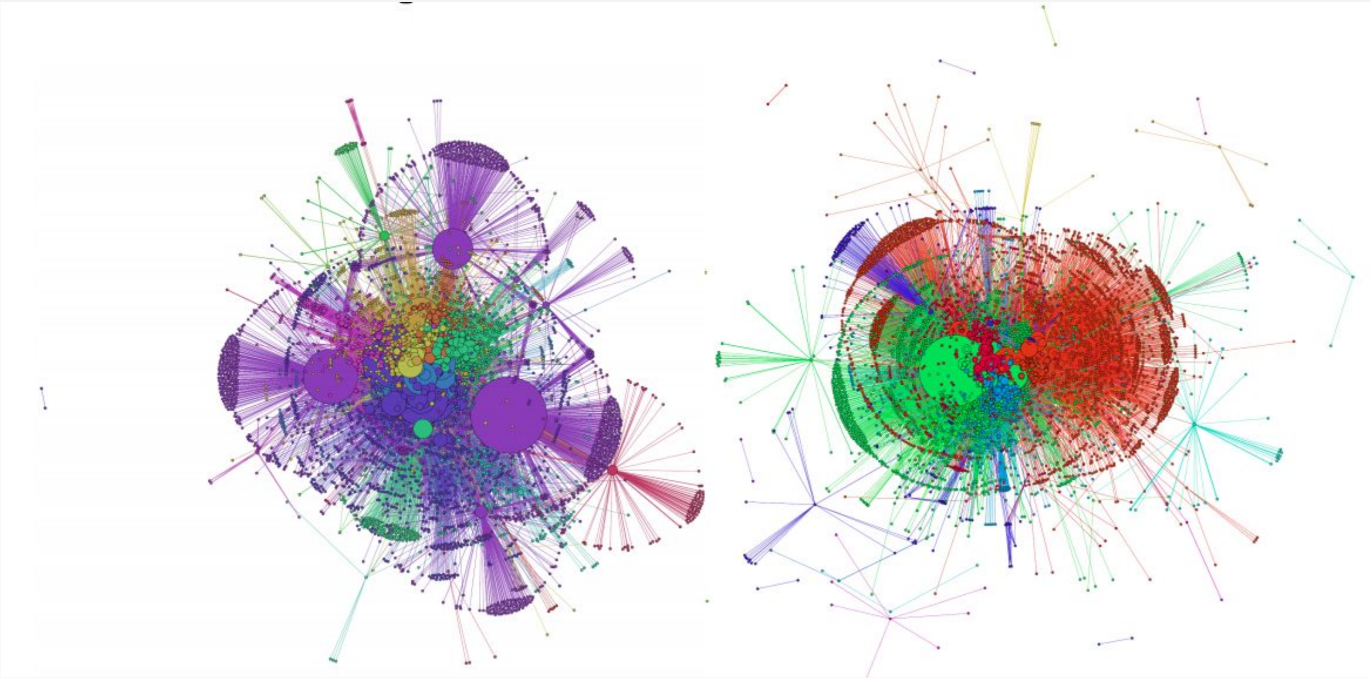
This research is the first to combine regulatory holding-level asset data for banks and insurers with private data for open-ended investment funds.

	IC	B	F	Total
Number of FI	139	24	1260	1423
Tot debt holdings (£bn)	643.7	1509.7	1100.9	3254.3
Mapped debt holdings/ tot debt holdings	0.90	0.86	0.73	0.82
Tot equity holdings (£bn)	582.8	68.6	925.3	1576.73
Mapped equity holdings/ tot equity holdings	0.81	0.93	0.78	0.80
Total Assets* (£tr)	1.6	6.5	10.2	

Common asset holding and systemic vulnerability across different financial institutions,
PB, T. Mahmood, L. Silvestri, Journal of Financial Stability

UCL

Common asset holding across financial institutions

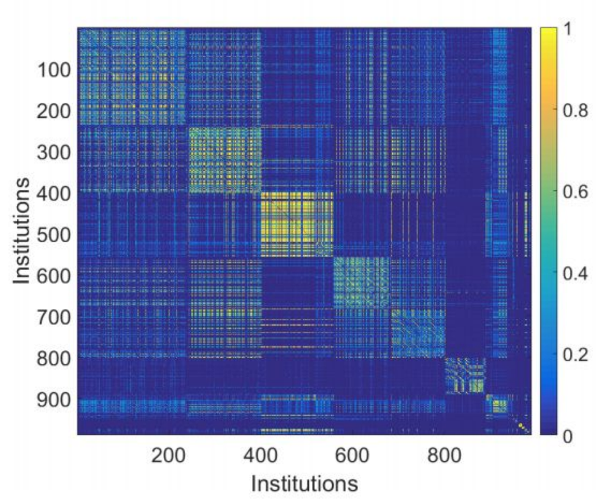


Bipartite networks of debt and equity holdings, institutions in the core are the most similar to one another.

Common asset holding across financial institutions

Main findings:

- Most financial institutions are far from complete diversification, only investment funds appear to be fully diversified in their equity holdings.
- There are large overlaps (leading to communities) in debt and equity security holdings.
- Non-unit linked insurers have debt holdings more similar to all other institution types; unit-linked insurers have equity holdings more similar to all other institution types.
- When considering liquidity of assets and under simple assumptions in a fire sale scenario, banks appear to be the most important ('central') on average.
- Both portfolio similarity and liquidity weighted portfolio overlap are useful tools for understanding vulnerabilities due to fire sales.



Monopartite similarity network (debt layer)

Common asset holding and systemic vulnerability across different financial institutions,
PB, T. Mahmood, L. Silvestri, Journal of Financial Stability

Pattern recognition of financial institutions’ payment behavior

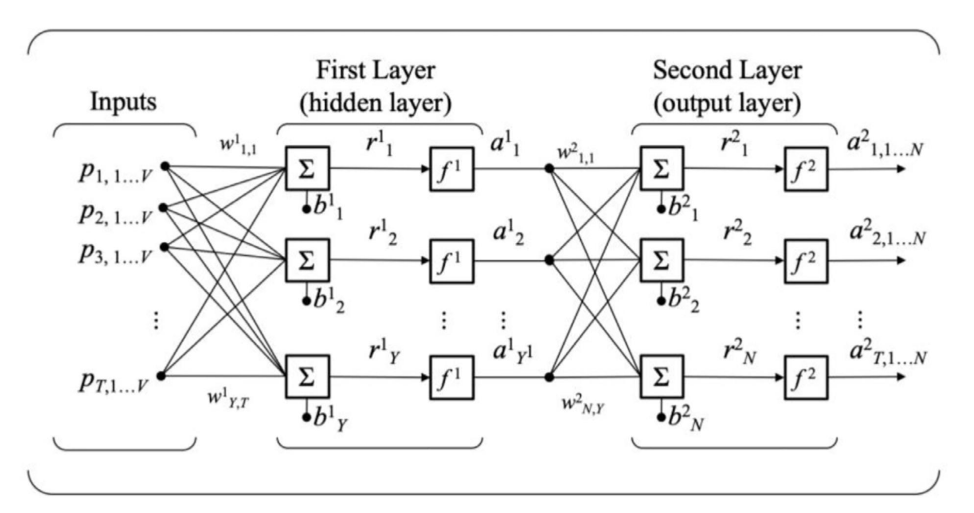
Main findings:

- We present a general supervised machine-learning methodology to represent the payment behavior of financial institutions starting from a database of transactions in the Colombian large-value payment system.
- The methodology learns a feedforward artificial neural network parameterization to represent the payment patterns through 113 features corresponding to financial institutions’ contribution to payments, funding habits, payment timing, payment concentration, centrality in the payment network, and systemic effects due to failure to pay.

Reference

León, Carlos, Paolo Barucca, Oscar Acero, Gerardo Gage, and Fabio Ortega. "Pattern recognition of financial institutions’ payment behavior." *Latin American Journal of Central Banking* 1, no. 1-4 (2020): 100011.

Pattern recognition of financial institutions’ payment behavior

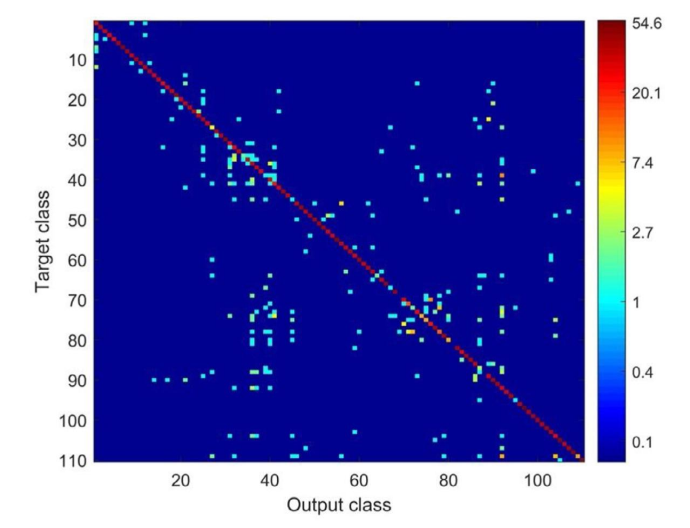


Multi-layer perceptron architecture for classifying institutions.

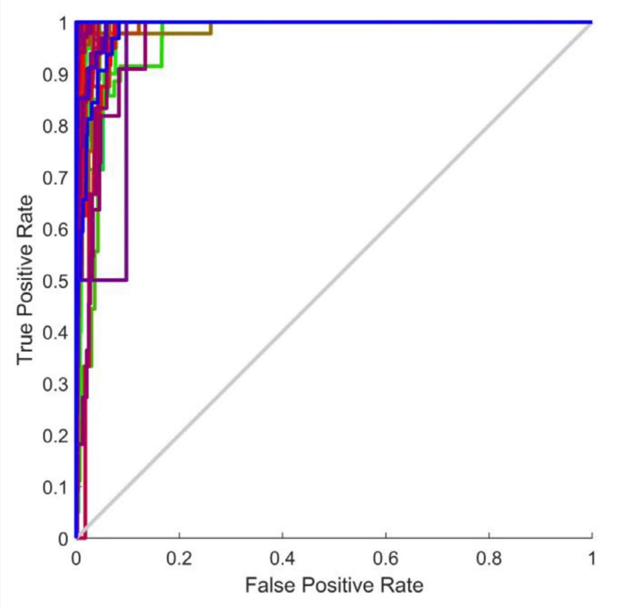
Reference

León, Carlos, Paolo Barucca, Oscar Acero, Gerardo Gage, and Fabio Ortega. "Pattern recognition of financial institutions’ payment behavior." *Latin American Journal of Central Banking* 1, no. 1-4 (2020): 100011.

Pattern recognition of financial institutions' payment behavior



Confusion matrix of the lowest classification errors, including all financial institutions.



ROC curve of the lowest classification error, including all financial institutions.

Reference

León, Carlos, Paolo Barucca, Oscar Acero, Gerardo Gage, and Fabio Ortega. "Pattern recognition of financial institutions' payment behavior." *Latin American Journal of Central Banking* 1, no. 1-4 (2020): 100011.

Models of temporal networks I

Snapshot models

Models of temporal networks I

Snapshot models

- DAR(p) discrete autoregressive processes
- SSI single snapshot inference
- TGRG temporally generalized random graphs
- DAR-TGRG discrete autoregressive temporally generalized random graphs
- Non-linear regression models with network features

The simplest model: DAR(1)

$$A_{ij}^t = V_{ij}^t A_{ij}^{t-1} + (1 - V_{ij}^t) Y_{ij}^t \quad \forall i, j = 1, ..., N \text{ and } j > i$$

- A is the adjacency matrix
- V and Y are Bernoulli variables

Temporally generalized random graphs (TGRG)

$$\theta_i^t = \phi_{0,i} + \phi_{1,i}\theta_i^{t-1} + \epsilon_i^t\,, \quad \forall i = 1, ..., N$$

$$\begin{cases} \mathbb{P}(\theta_i^t | \theta_i^{t-1}, \boldsymbol{\Phi}_i) & = f(\theta_i^t | \phi_{0,i} + \phi_{1,i}\theta_i^{t-1}, \sigma_i^2) \quad \forall i = 1, ..., N \\ \mathbb{P}(\boldsymbol{A}^t | \Theta^t) & = \prod_{i,j>i} \mathbb{P}(A_{ij}^t | \theta_i^t, \theta_j^t) = \prod_{i,j>i} \frac{e^{A_{ij}^t(\theta_i^t + \theta_j^t)}}{1+e^{(\theta_i^t+\theta_j^t)}} \end{cases}$$

- AR(1) model for the fitness parameters
- No link copying mechanism
- The memory is only in the fitness parameters

DAR-TGRG

$$\begin{cases} \mathbb{P}(\theta_i^t | \theta_i^{t-1}, \mathbf{\Phi}_i) & = f(\theta_i^t | \phi_{0,i} + \phi_{1,i}\theta_i^{t-1}, \sigma_i^2) \quad \forall i = 1, ..., N \\ \mathbb{P}(\boldsymbol{A}^t | \boldsymbol{A}^{t-1}, \Theta^t, \boldsymbol{\alpha}) & = \prod_{i,j>i} \left(\alpha_{ij} \mathbb{I}_{A_{ij}^t A_{ij}^{t-1}} + (1 - \alpha_{ij}) \frac{e^{A_{ij}^t (\theta_i^t + \theta_j^t)}}{1 + e^{(\theta_i^t + \theta_j^t)}} \right) \end{cases}$$

- AR(1) model for the fitness parameters
- Link copying mechanism
- The memory is both in the fitness parameters and in the sampled matrices

Expectation Maximization

(1) Assume as starting point $\tilde{\mathbf{\Theta}}$ and $\tilde{\Pi} = \{\tilde{\mathbf{\Phi}}, \tilde{\boldsymbol{\alpha}}\}$.
(2) Infer $\hat{\mathbf{\Theta}} \equiv \{\hat{\Theta}^t\}^{t=1,\ldots T}$ by solving Eq. 2.7 with $\tilde{\Pi}$.
(3) Learn $\hat{\boldsymbol{\alpha}}$ by solving Eq. 2.14 for each possible couple of nodes with previously inferred $\hat{\mathbf{\Theta}}$ and $\tilde{\mathbf{\Phi}}$.
(4) Learn $\hat{\mathbf{\Phi}}$ by solving Eq. 2.18 for each i with previously inferred $\hat{\mathbf{\Theta}}$ and $\hat{\boldsymbol{\alpha}}$.
(5) Update $\tilde{\mathbf{\Theta}} \leftarrow \hat{\mathbf{\Theta}}$.
(6) Update $\tilde{\Pi} \leftarrow \hat{\Pi}$.
(7) Repeat until convergence.

Recognising preferential trading and predicting links

Research question:

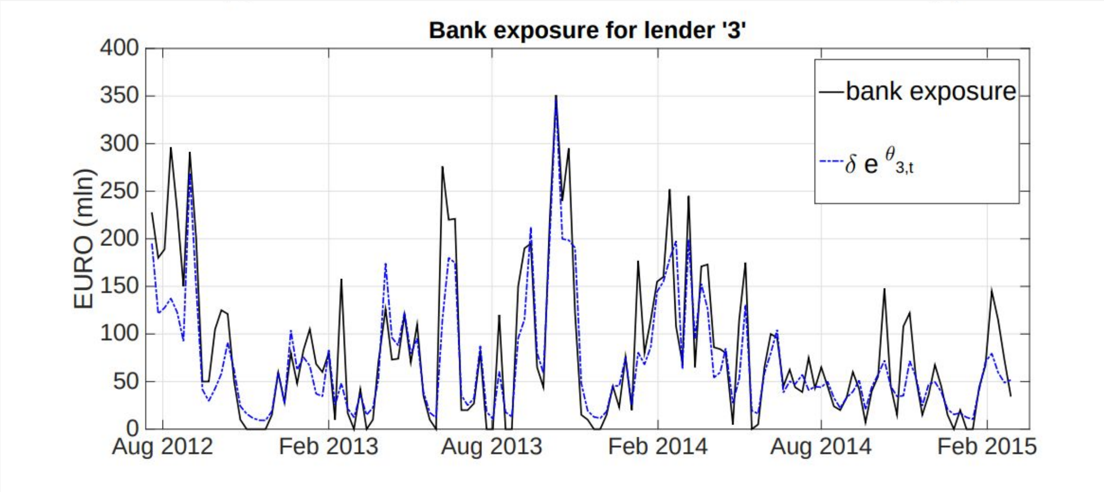
- Can we provide an analytic model of dynamic networks that would account for their persistence?
- Can we calibrate such model efficiently and predict future links, i.e. future transactions in the case of an interbank market?

Methodology:

- Fitness model generating networks with an arbitrary degree distribution
- Markov Process for the latent variables and for individual links

$$\begin{cases} \mathbb{P}(\theta_i^t|\theta_i^{t-1}, \mathbf{\Phi}_i) & = f(\theta_i^t|\phi_{0,i} + \phi_{1,i}\theta_i^{t-1}, \sigma_i^2) \quad \forall i = 1, ..., N \\ \mathbb{P}(\boldsymbol{A}^t|\boldsymbol{A}^{t-1}, \Theta^t, \boldsymbol{\alpha}) & = \prod_{i,j>i} \left(\alpha_{ij} \mathbb{I}_{A_{ij}^t, A_{ij}^{t-1}} + (1-\alpha_{ij}) \frac{e^{A_{ij}^t(\theta_i^t + \theta_j^t)}}{1+e^{(\theta_i^t + \theta_j^t)}} \right) \end{cases}$$

Time-varying fitness

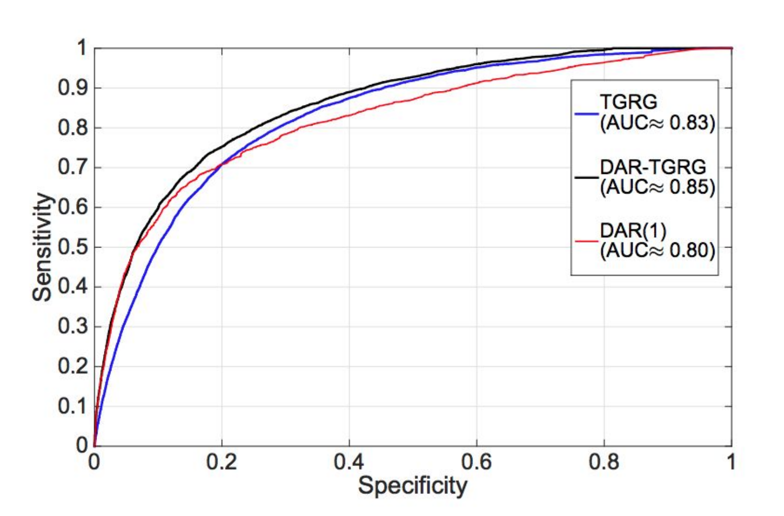


An example of time-varying fitness compared with the bank exposure for a given bank

Recognising preferential trading and predicting links

Main findings:

- The empirical results allow us to recognise preferential lending in the interbank market,
- A method that does not account for time-varying network topologies tends to overestimate preferential linkage.



True positive rate (sensitivity) vs true negative rate (specificity) in link prediction

Reference:

Mazzarisi, Piero, Paolo Barucca, Fabrizio Lillo, and Daniele Tantari. "A dynamic network model with persistent links and node-specific latent variables, with an application to the interbank market." *European Journal of Operational Research* 281, no. 1 (2020): 50-65.

Structural edge importance in capital markets transactions

Main findings:

- We define a structural importance metric, le, for the edges of a network.
- The metric is based on perturbing the adjacency matrix and observing the change in its largest eigenvalues.
- We propose a model of network evolution where this metric controls the probabilities of subsequent edge changes.

$$l_e = \frac{\partial \lambda}{\partial A_{ij}}$$

$$A_{ij}^{t+1} = \mathcal{V}_{ij}^{t} A_{ij}^{t} \mathcal{U}_{ij}^{t} + \left(1 - \mathcal{V}_{ij}^{t}\right) A_{ij}^{t}$$

Reference:

Seabrook, Isobel E., Paolo Barucca, and Fabio Caccioli. "Evaluating structural edge importance in temporal networks." *EPJ Data Science* 10, no. 1 (2021): 23.

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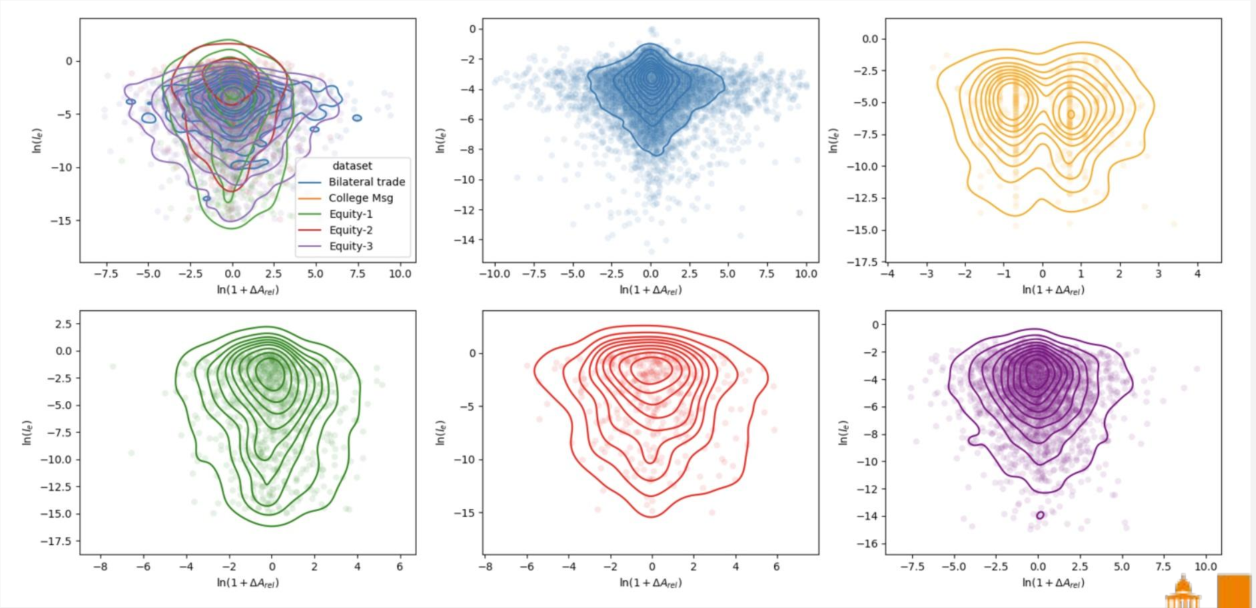
Structural edge importance in capital markets transactions

We show using synthetic data how the parameters of the model are related to the capability of predicting whether an edge will change from its value of le.



Structural edge importance in capital markets transactions

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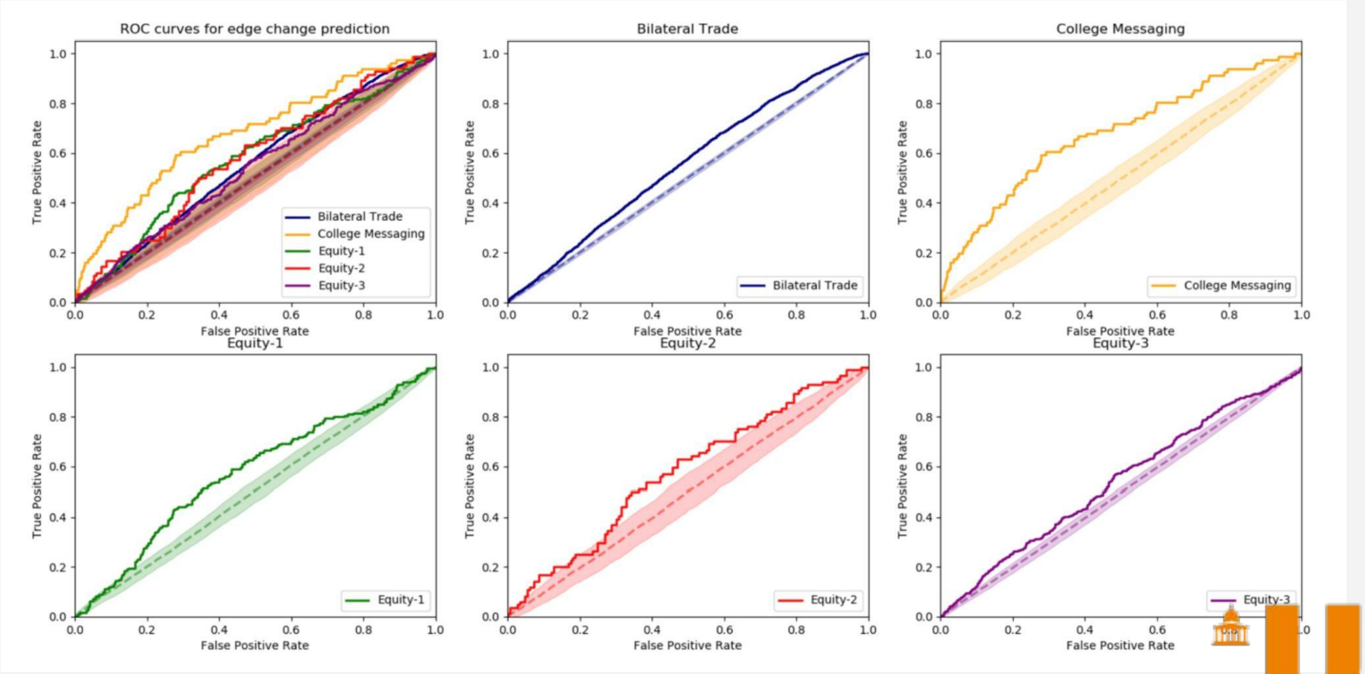


Models of temporal networks II

Timestamped models

Hawkes processes for busty transactions

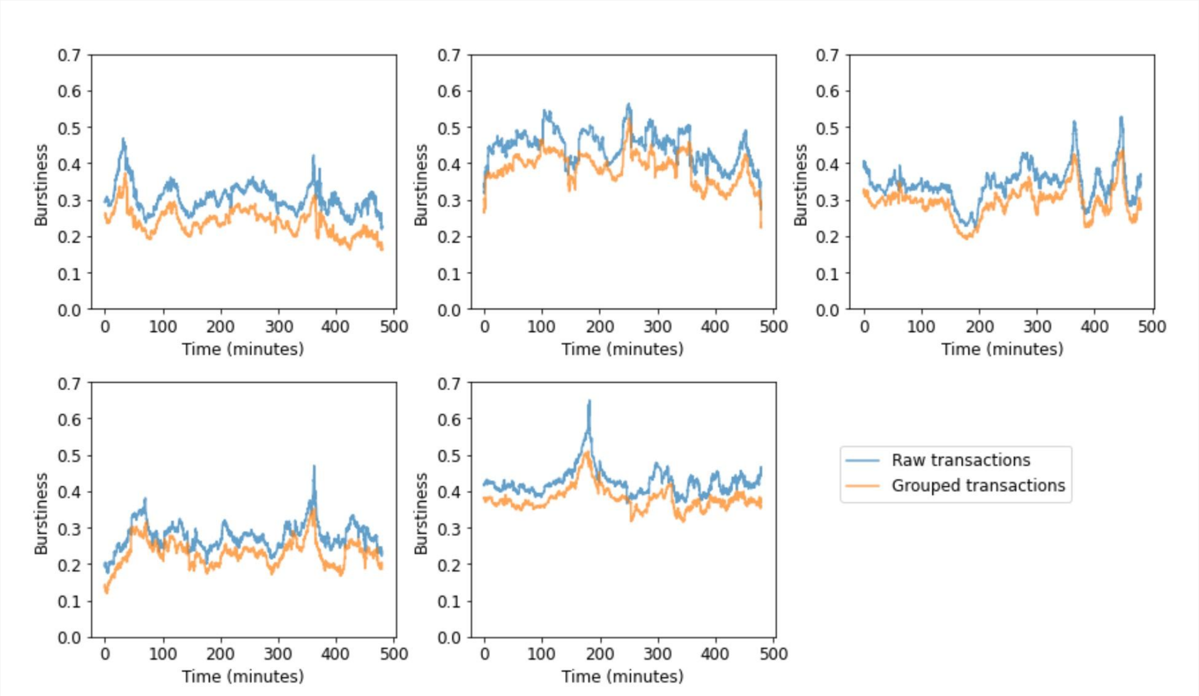
Main findings:

- we use transaction reports for five FTSE 100 stocks,
- we fit Hawkes processes at the overall transaction level, at the level of individual counterparty relationships, and for trades executed via central clearing counterparties
- we generate synthetic transaction sequences which display similar properties to real transaction sequences.
- we quantify burstiness depending on the number of hubs (CCPs) in the transaction networks

Reference:

Seabrook, Isobel E., Paolo Barucca, and Fabio Caccioli. "Modeling equity transaction networks as bursty processes" *Working Paper*

Hawkes processes for busty transactions



Reference:

Seabrook, Isobel E., Paolo Barucca, and Fabio Caccioli. "Modeling equity transaction networks as bursty processes" *Working Paper*

Hawkes process for busty transactions

$$\lambda(t) = \mu + \sum_{t_k < t} \phi(t - t_k)$$

$$\mathcal{L} = \log \frac{\prod_{i=1}^{n} \lambda(t_i)}{\exp \int_0^T \lambda(t) dt} = \sum_{i=1}^{n} \log \lambda(t_i) - \int_0^T \lambda(t) dt$$

Reference:

Seabrook, Isobel E., Paolo Barucca, and Fabio Caccioli. "Modeling equity transaction networks as bursty processes"
Working Paper

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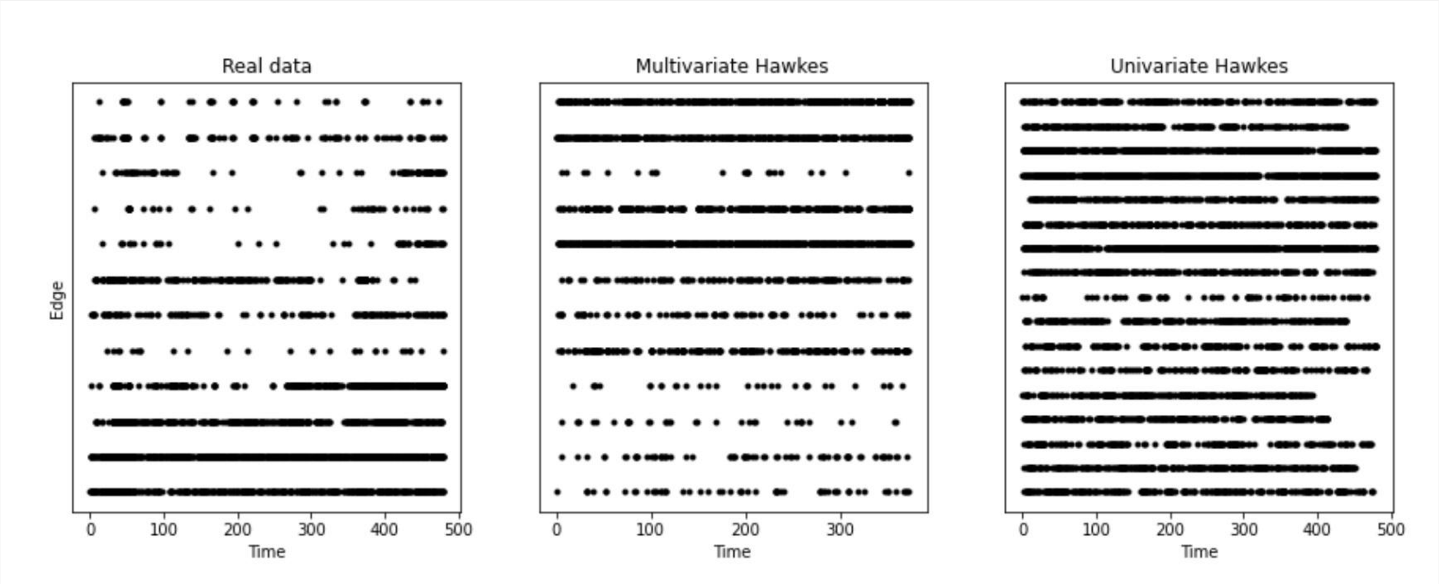
Multivariate Hawkes processes for busty transactions

$$\lambda_t^i = \mu^i + \sum_{i=1}^{D} \int \mathrm{d}N_{t'}^j \phi^{ij}(t - t')$$

Reference:

Seabrook, Isobel E., Paolo Barucca, and Fabio Caccioli. "Modeling equity transaction networks as bursty processes"
Working Paper

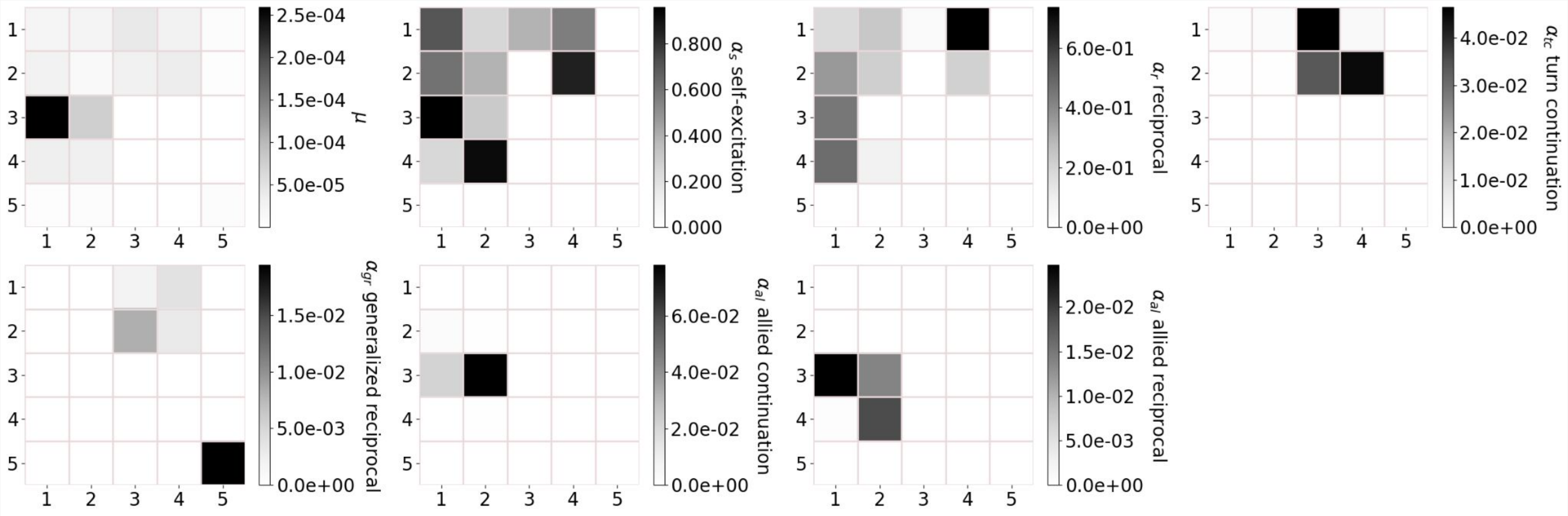
Hawkes processes for busty transactions



Reference:

Seabrook, Isobel E., Paolo Barucca, and Fabio Caccioli. "Modeling equity transaction networks as bursty processes"
Working Paper

Parsimonious Hawkes Processes for temporal networks modelling



Reference:

Yuwei Zhu and Paolo Barucca"Modeling equity transaction networks as bursty processes" *Working Paper*

Perspectives

- Can we find a compromise between a realistic generative and inference model and a simple unified picture for decision making under uncertainty in stability and systemic risk?
- Can we isolate risk sources in networks before they become systemic thanks to network theory and machine learning?
- Can we identify general stability criteria for a broad range of non-linear dynamical systems?

Questions, comments or ideas?

Contact me at p.barucca (at) ucl.ac.uk

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