CHARACTERIZING THE DYNAMICS OF FINANCIAL NETWORKS

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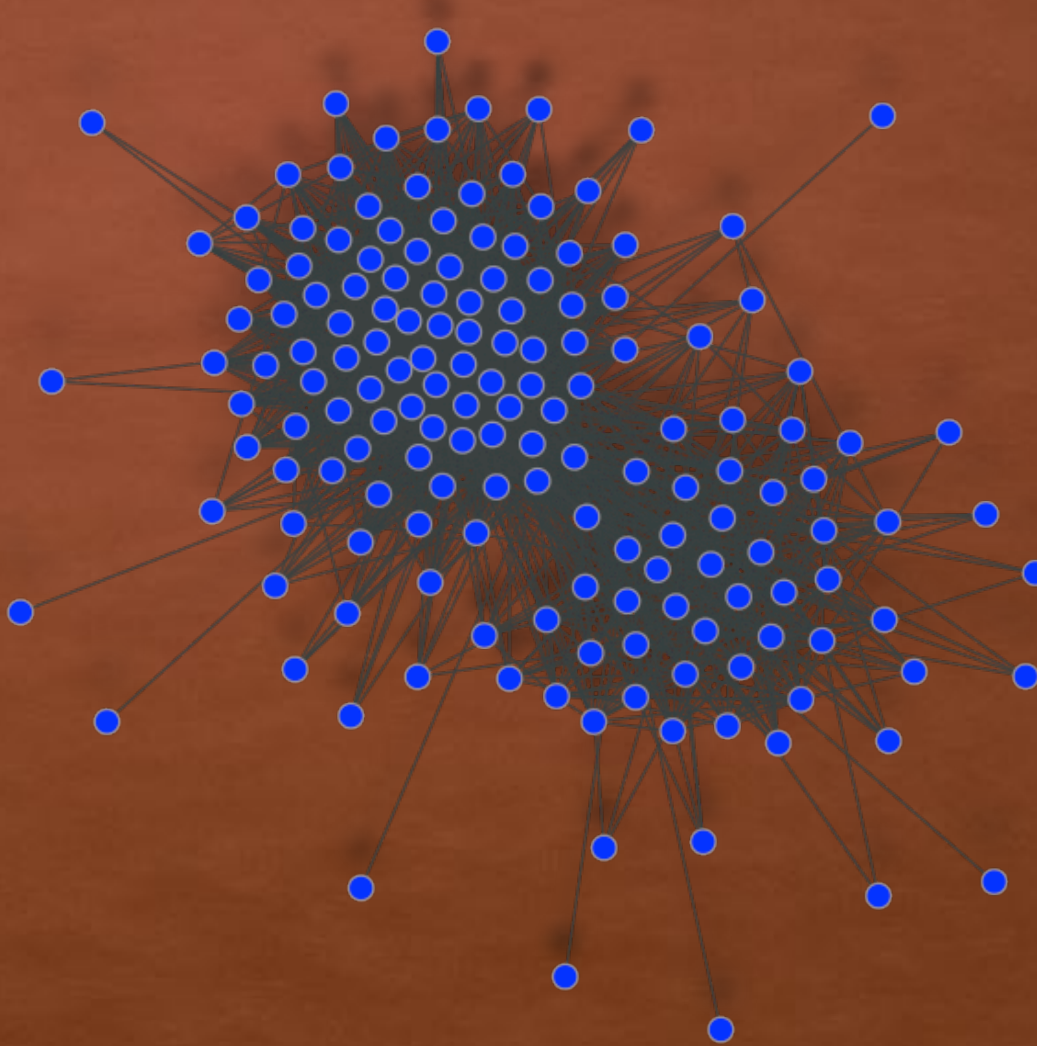


Introduction of myself

Background: Macroeconomics, Monetary policy
Recent research interest: Complex networks, financial systemic risk, social networks

Collaborators:

Physics:
N. Masuda (NYS Buffalo)
T. Takaguchi (LINE Corp.)
A. Barrat (CNRS)

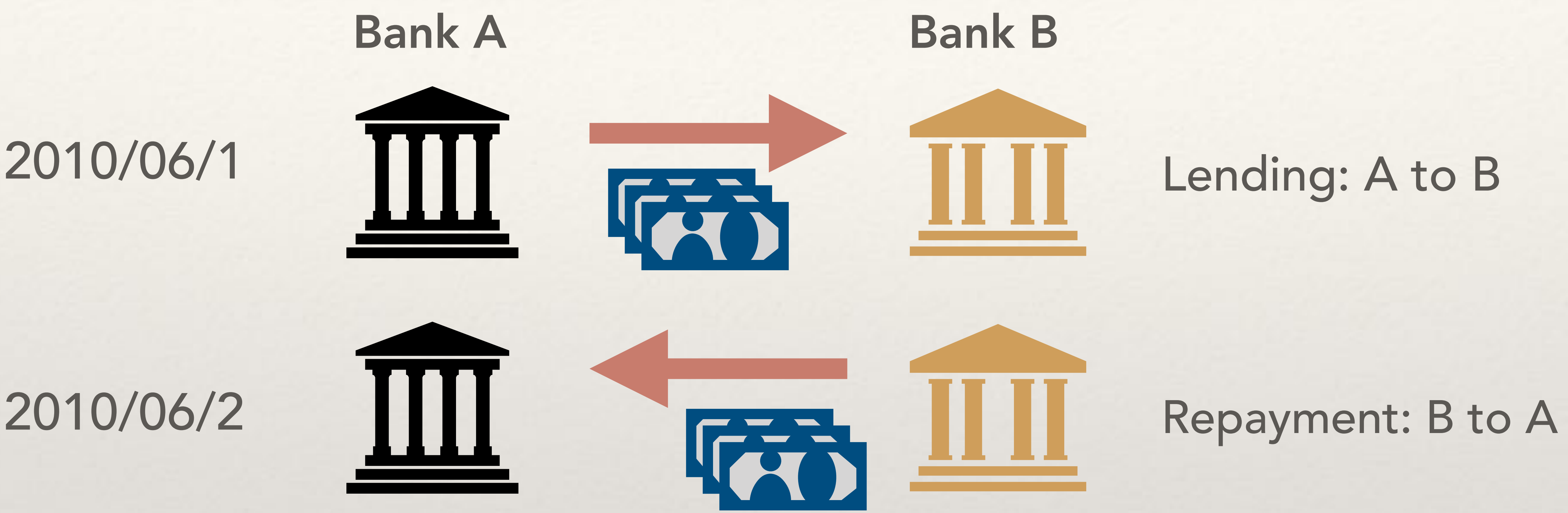
Applied Math:
C.D. Brummitt
T. Yaguchi (Kobe U, PRESTO)

CS:
E. Ferrara (USC)
A. Sapienza (USC)

Econ:
Muto (BOJ)
T. Sugo (BOJ) etc.

1. Data analysis of interbank networks

Temporality of interbank networks



- Overnight transactions form daily networks
- Network structure changes day to day

Conventional approach of interbank network analysis

- Overnight lending-borrowing, but aggregate networks (weekly, monthly, etc.)

- Why aggregated?

Are networks random at the daily scale?

"We show that the **networks appear to be random at the daily level**, but contain significant non-random structure for longer aggregation periods."

- Finger, Fricke, and Lux, 2013, Comput. Manag. Sci.

"For the e-mid, **we initially looked at daily snapshot** of loans among banks. However, we found that the **high volatility of the links at this time scale prevented a robust estimation of the network properties**."

- Musmeci, Battiston, Caldarelli, Puliga, Gabrielli., 2013, J. Stat. Phys.

Objective of this work

- **Characterize dynamical patterns at the daily scale!**

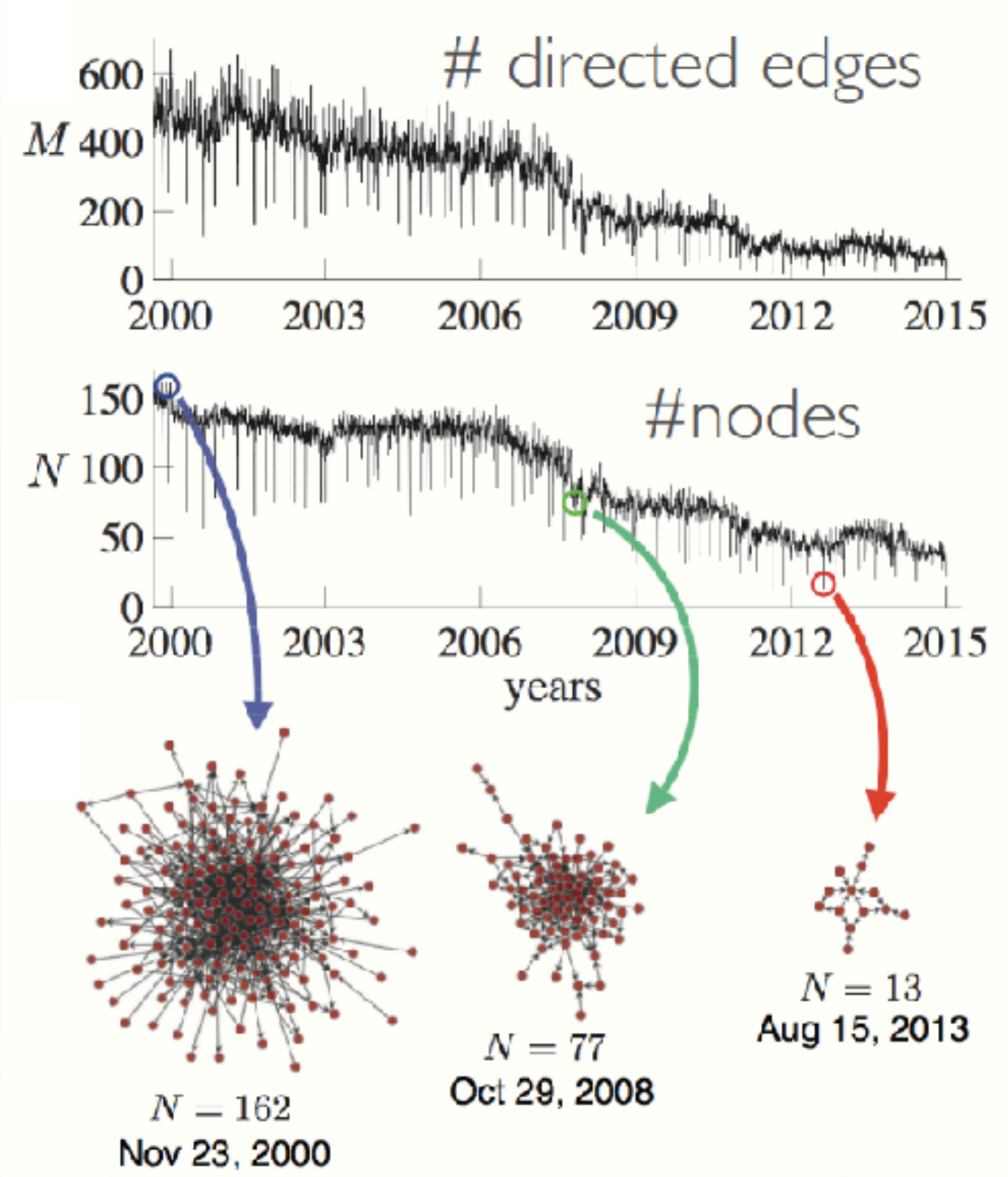
Data: e-MID (Italian interbank market)

Sample

Duration	Time	Rate	Amount	Quoter	Agressor	Verb
ON	2000-09-04 09:06:00	4.62	5	IT0159	IT0094	Buy

Duration	ON (overnight), ONL (overnight large)
Data period	Sep, 2000 - Dec, 2015 (3922 business days)
# banks	308 (in total)
# transactions	1,187,415

Size of daily networks



- **Network size varies daily**
- **Non-stationary (downward trends)**

Max: $N = 162$

Min: $N = 13$

Daily dynamical patterns

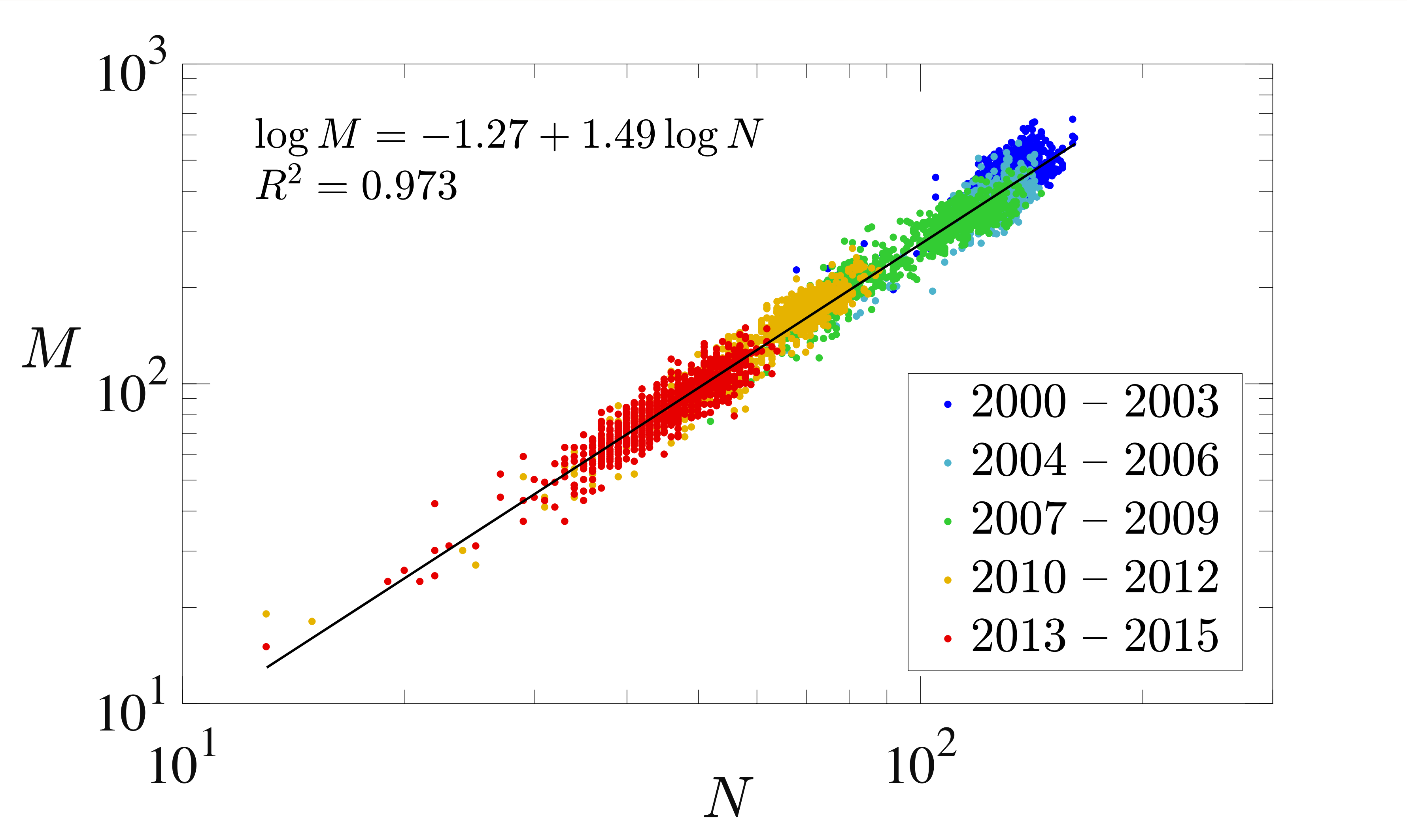
1. Size and the # of edges

$$M \propto N^{1.5}$$

$$\langle k \rangle \propto \sqrt{N}$$

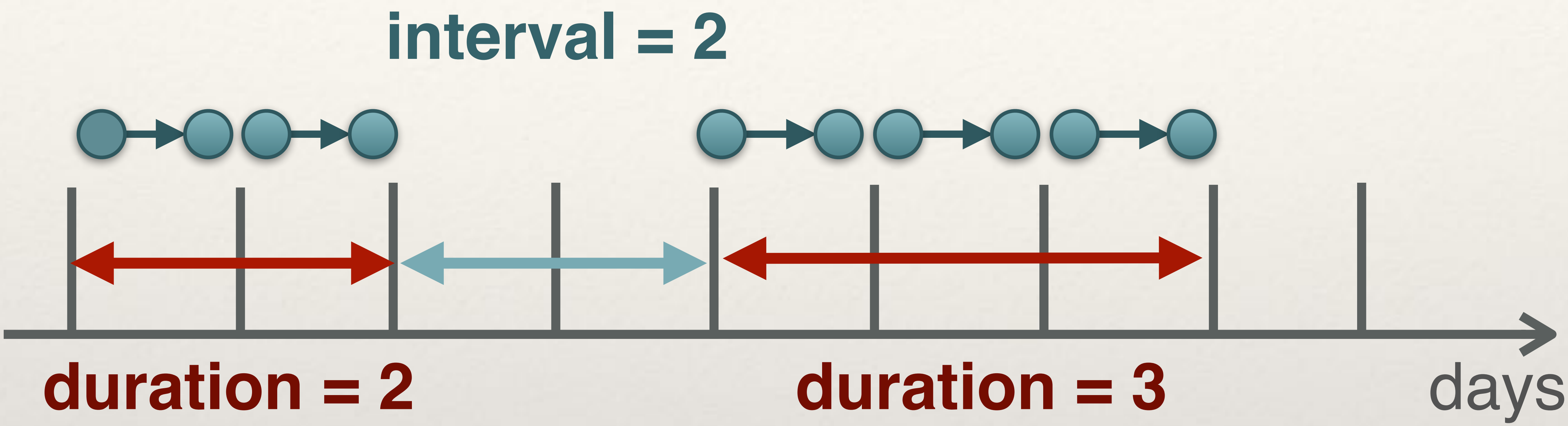
"Superlinear scaling"

edges

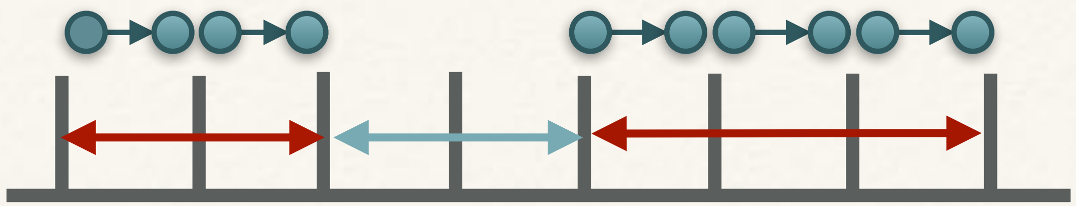


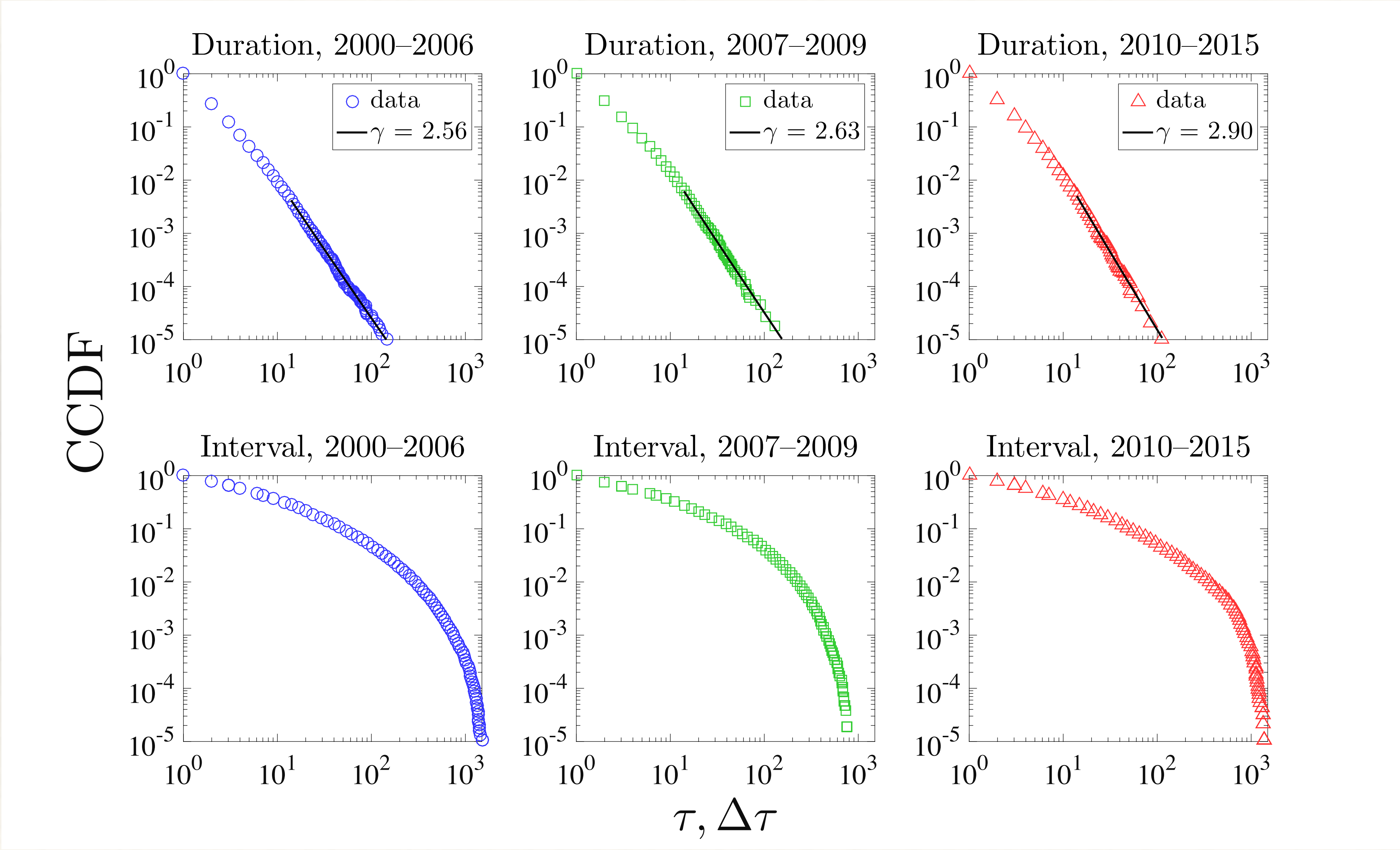
nodes

2. Duration and interval time (days)



Duration and interval time (for pairs)



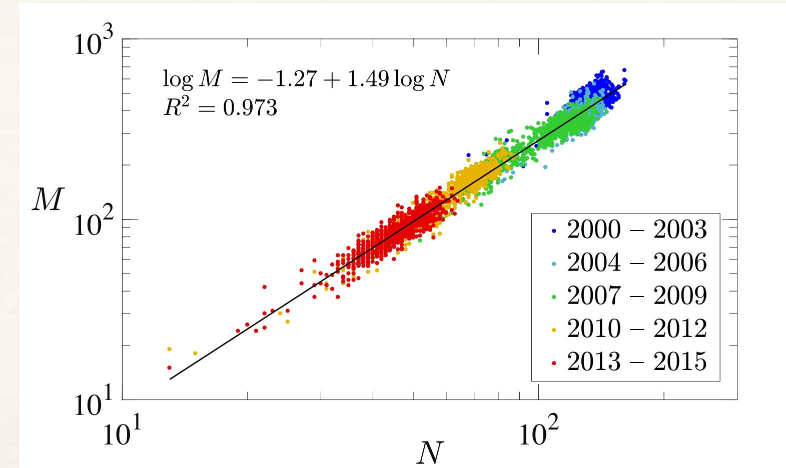


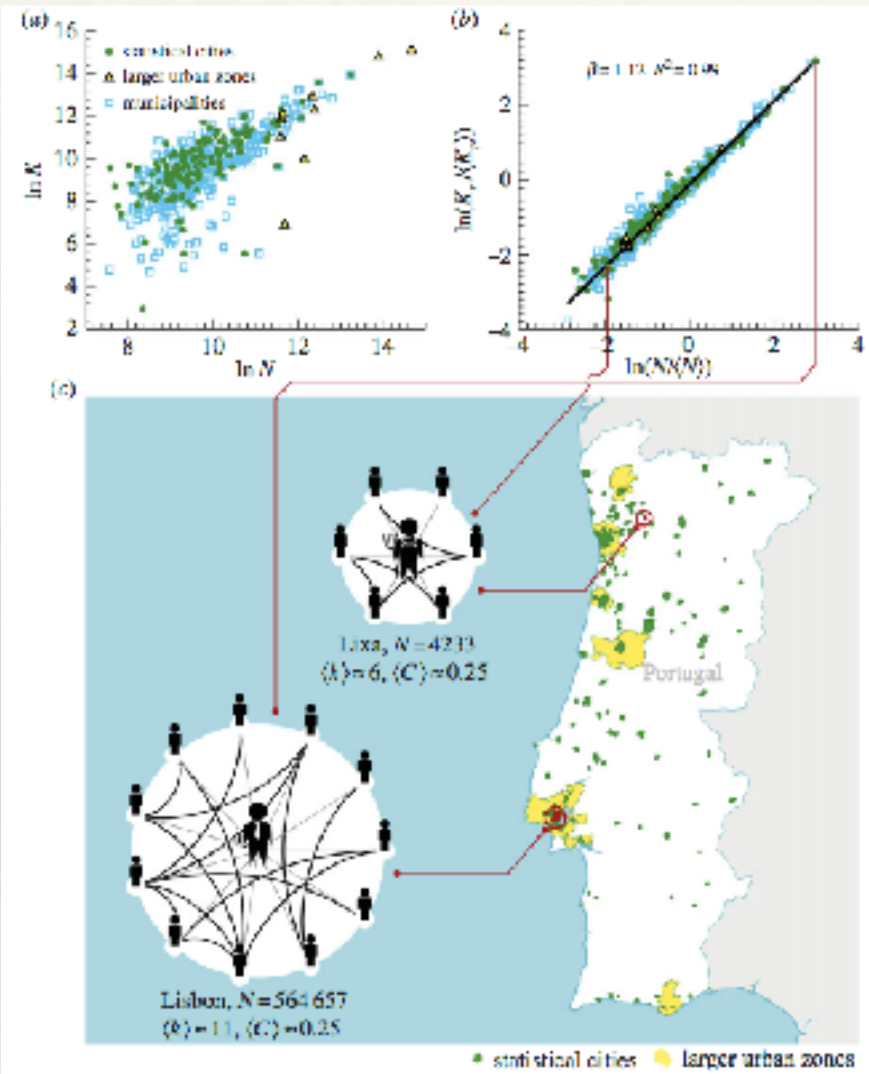
days

Social systems

Similarity to social networks:

Superlinear scaling





Schläpfer et al, J. Roy. Soc. Interface, 2014

1. # of mobile phone users vs. # of pairs
2. Population vs. time of calls

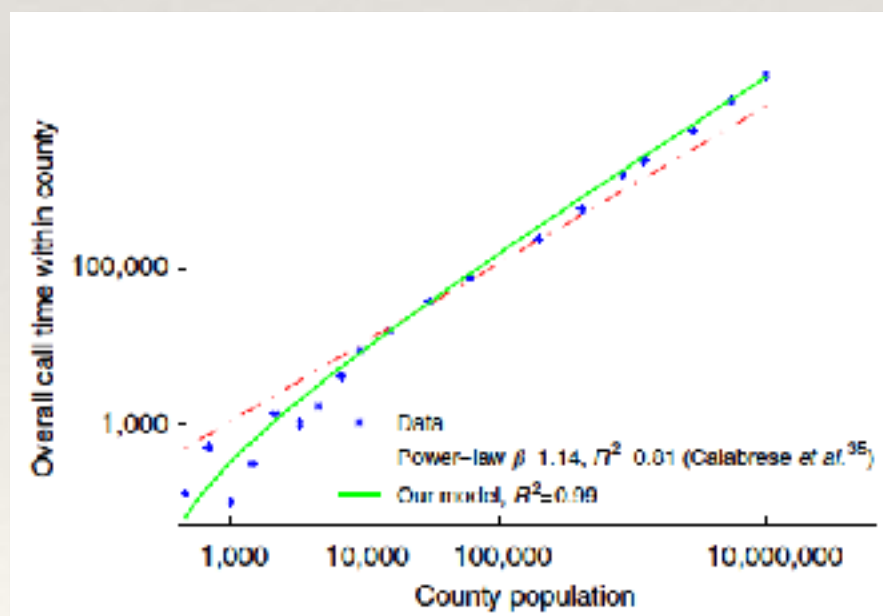
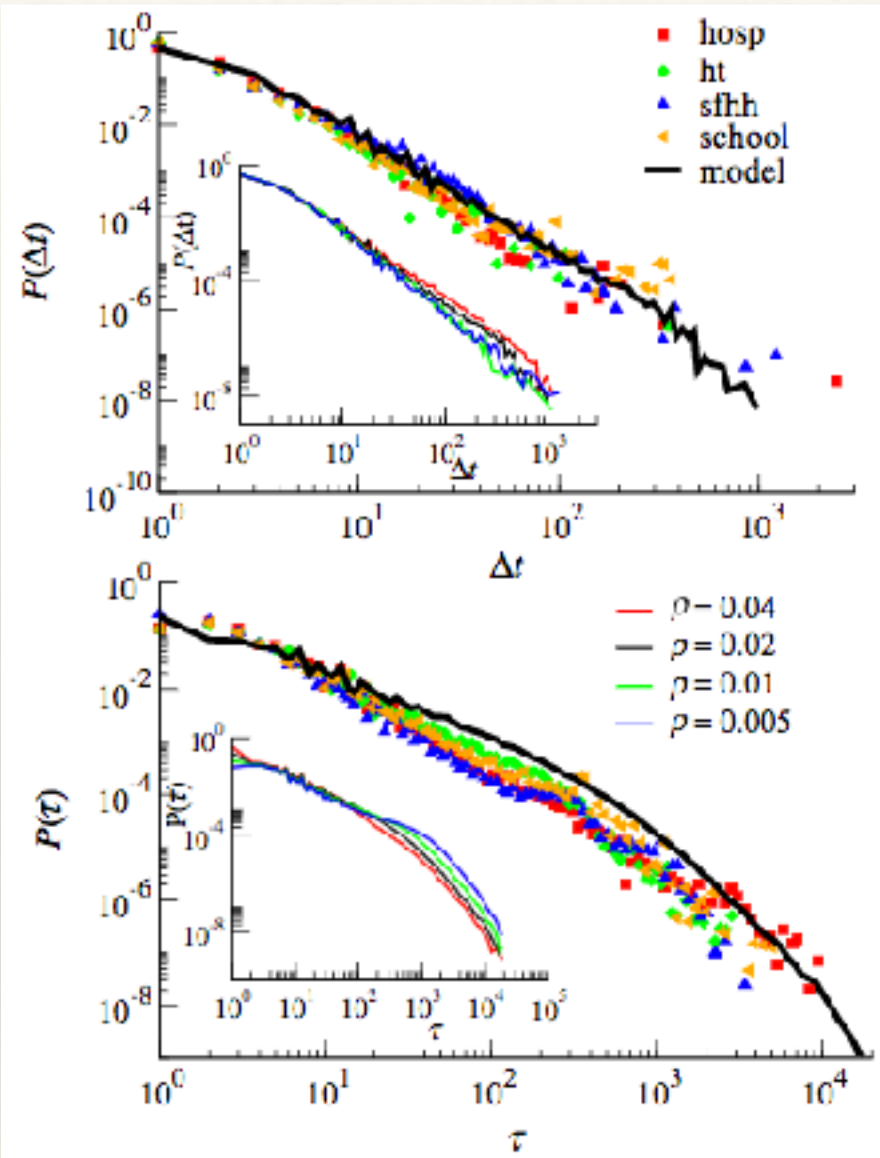


Figure 2 | Overall time of calls between residents of a county as a function of its population. The points refer to the data (adapted from

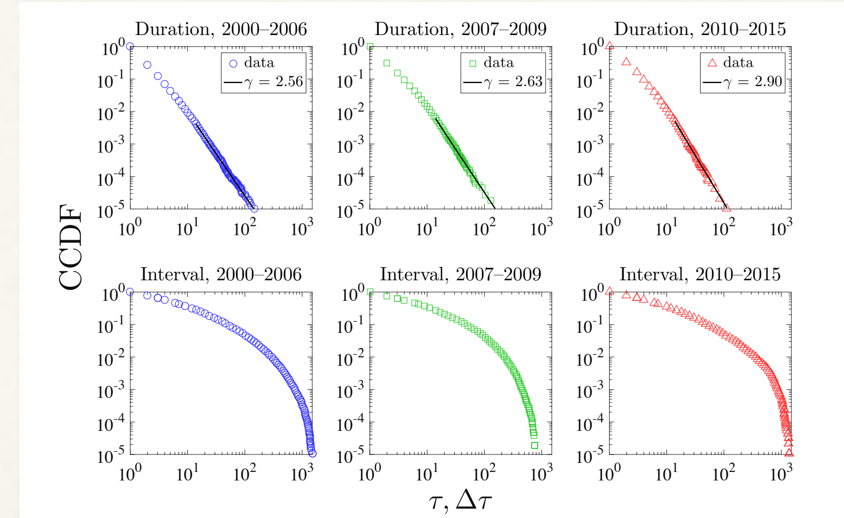
Pan et al, Nature Communications, 2013

Similarity to social networks:

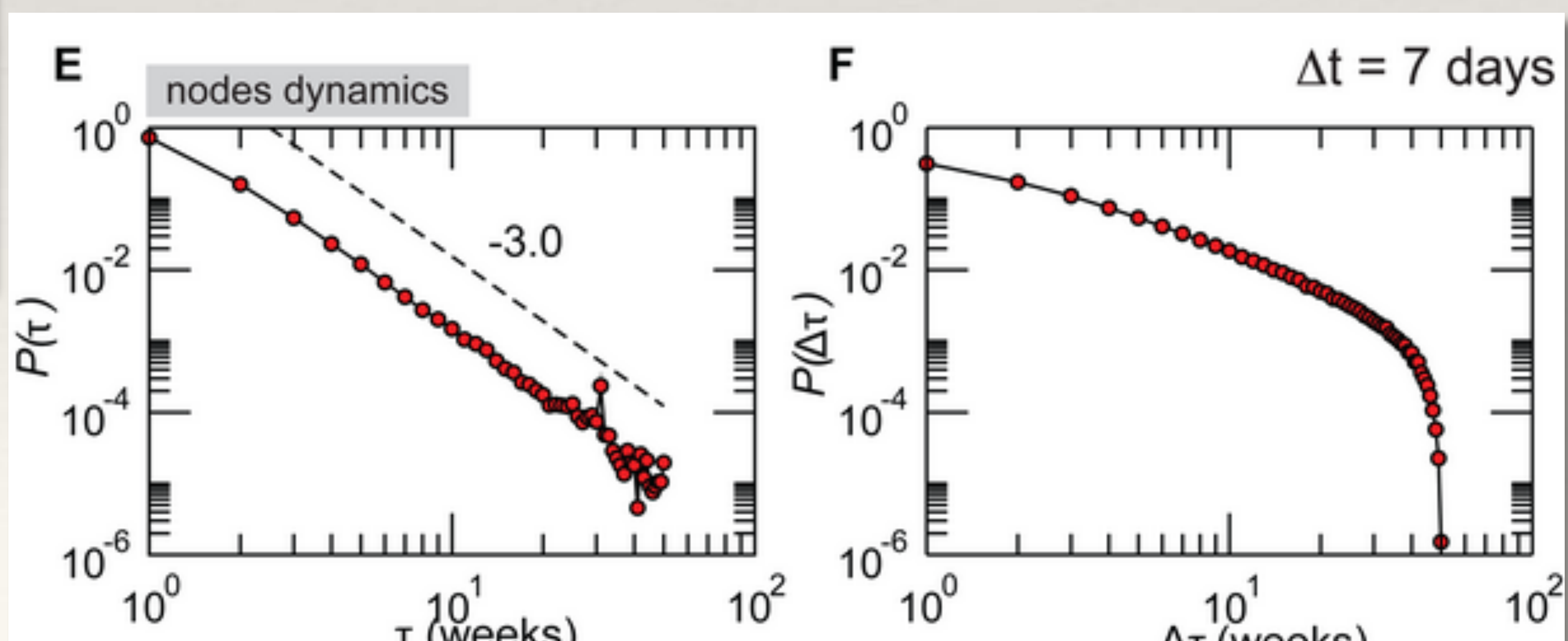
Duration and interval time



Starnini et al. PRL 2013



1. Face-to-face interaction
2. Cattle trade movements between livestock premises



Bajardi et al., PLOS ONE 2011

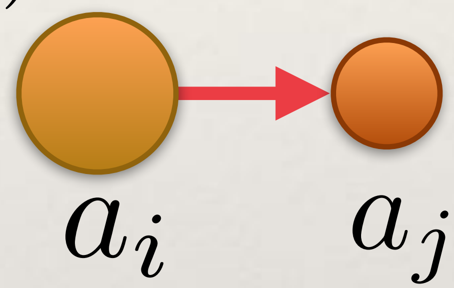
Model

Model: A dynamic Fitness Model

Step 0. There are N_{p} many isolated banks

Bank i has activity $a_i \in [0, 1]$

Step 1. Edge creation with prob. $p_{ij} = (a_i a_j)^{\alpha}$



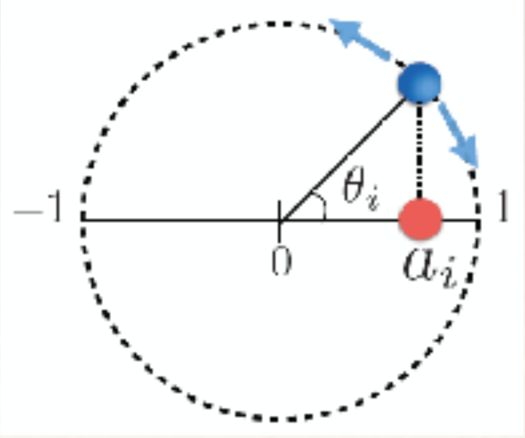
Step 2. Update activity

with prob. h $\rightarrow$ redraw a_i from $\mathrm{U}[0,1]$

with prob. 1-h $\rightarrow$ update as $a_i = |\cos \theta_i|$

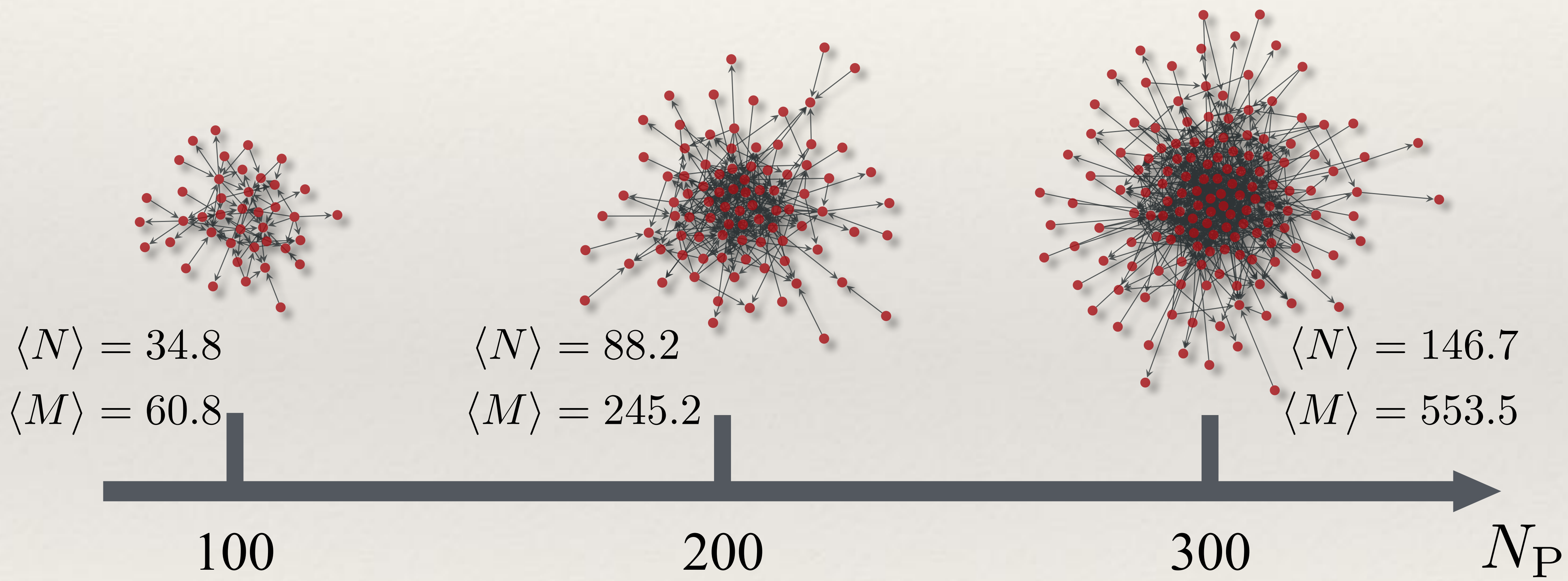
→ Go to **Step 0.**

θ_i : random walk



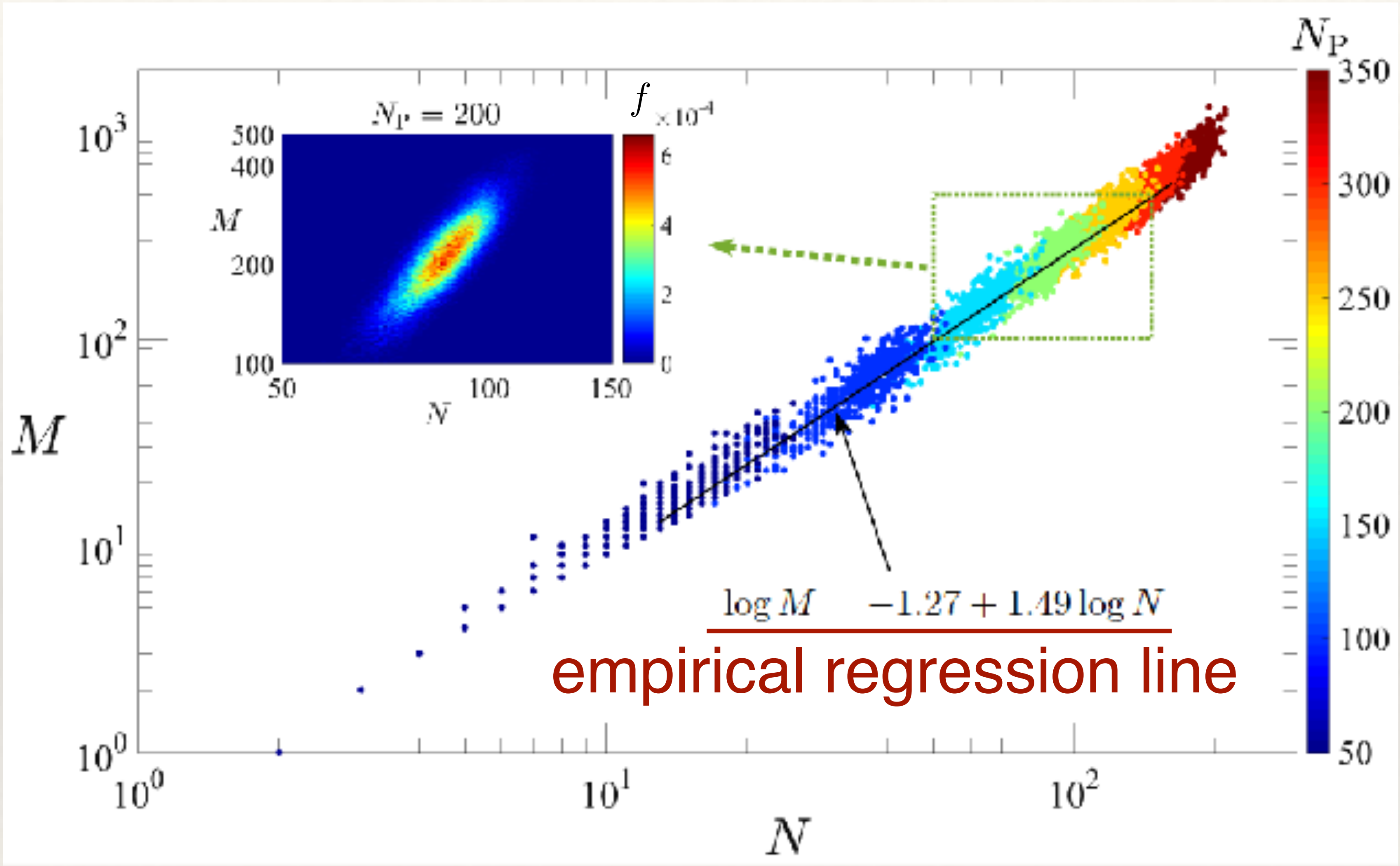
Synthetic networks

- N_{p} controls the average size of networks



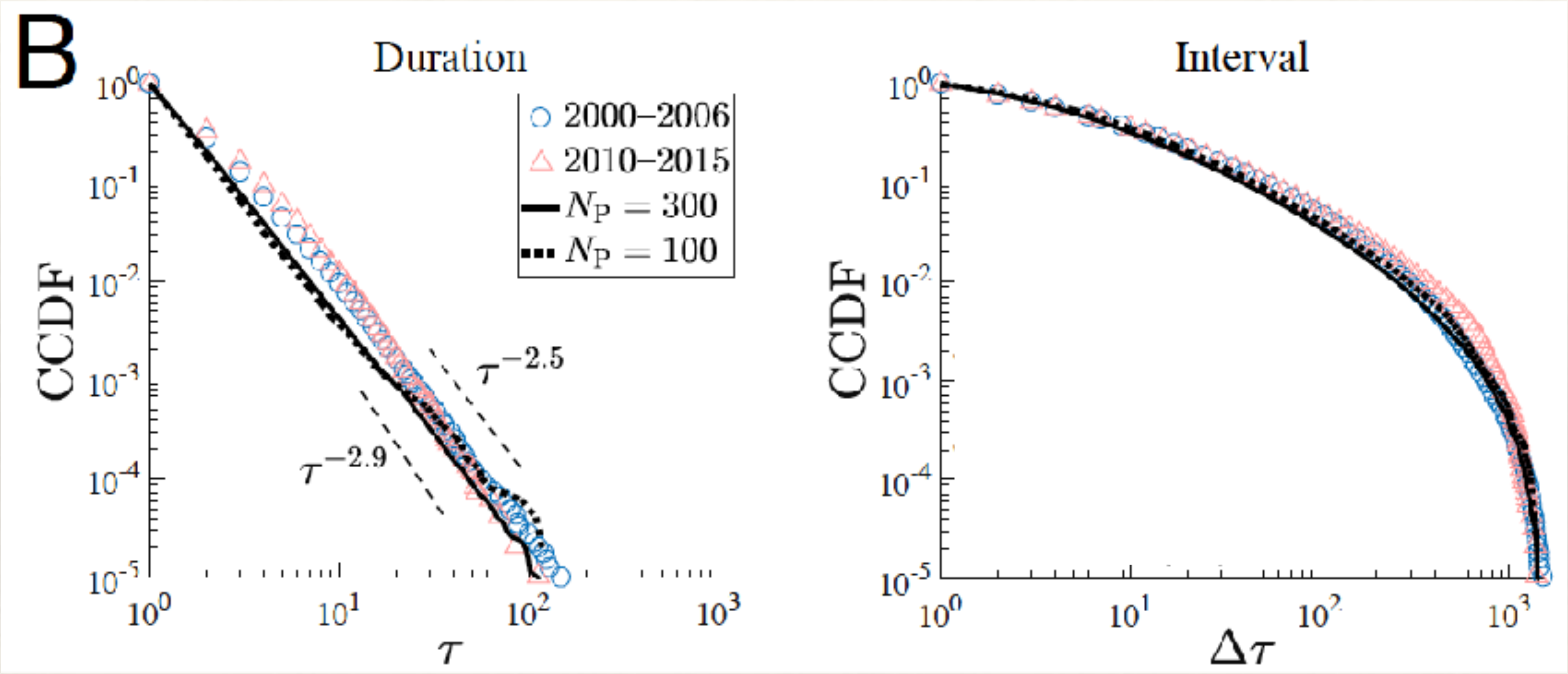
Visualized by graph-tool

Result: Emergence of superlinear scaling



Result: duration and interval (pairwise)

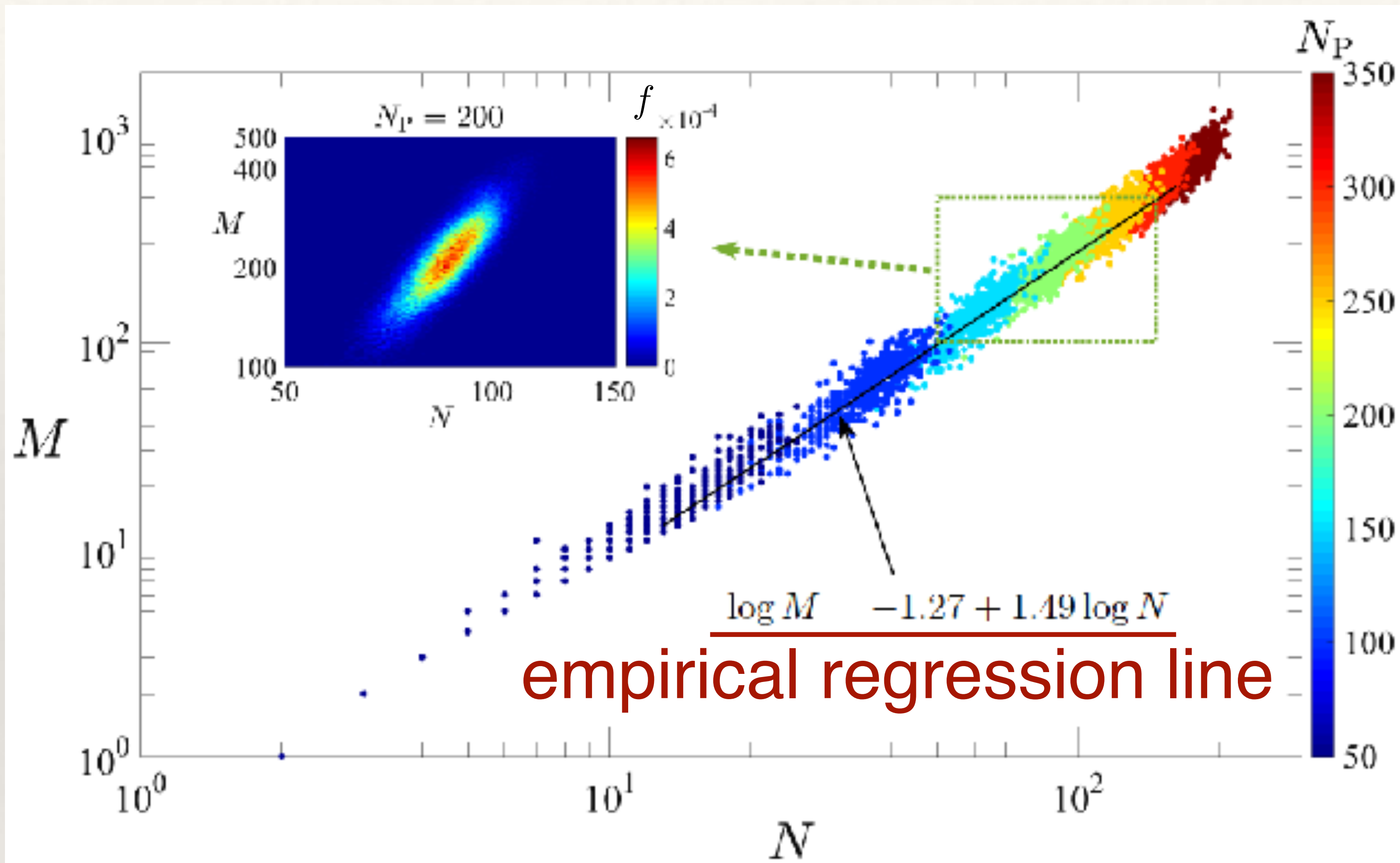
Data (symbol) and model (line)



For a given N_{p}, a sequence of «daily» networks is generated

Estimating the potential network size N_p

Simulated histogram: $f(N, M|N_\mathrm{p})$

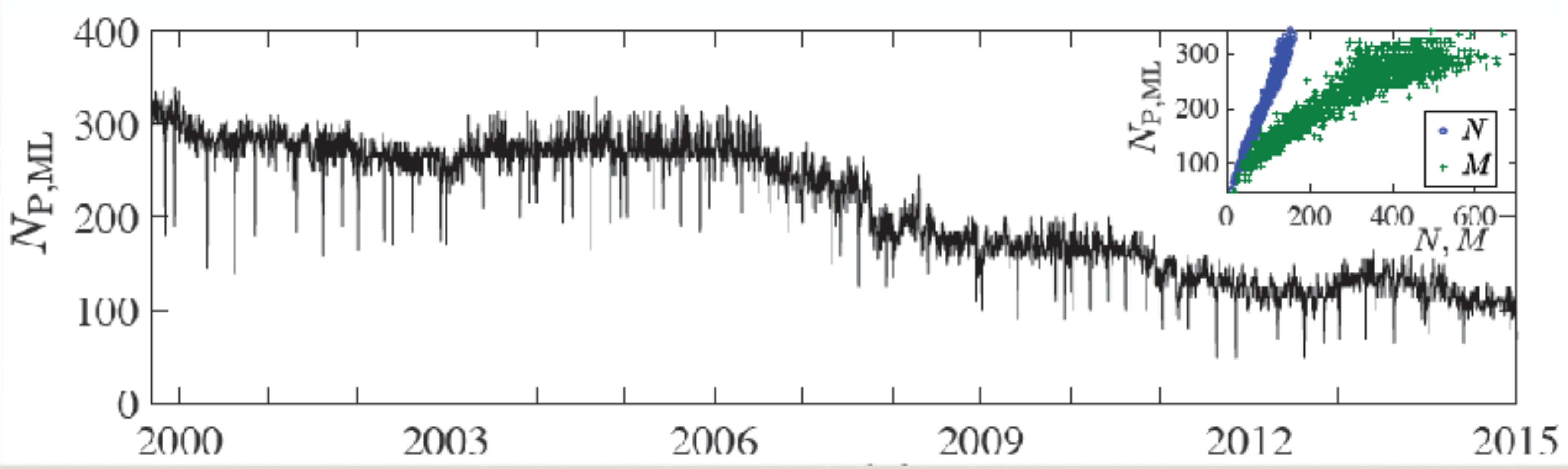


ML estimator:

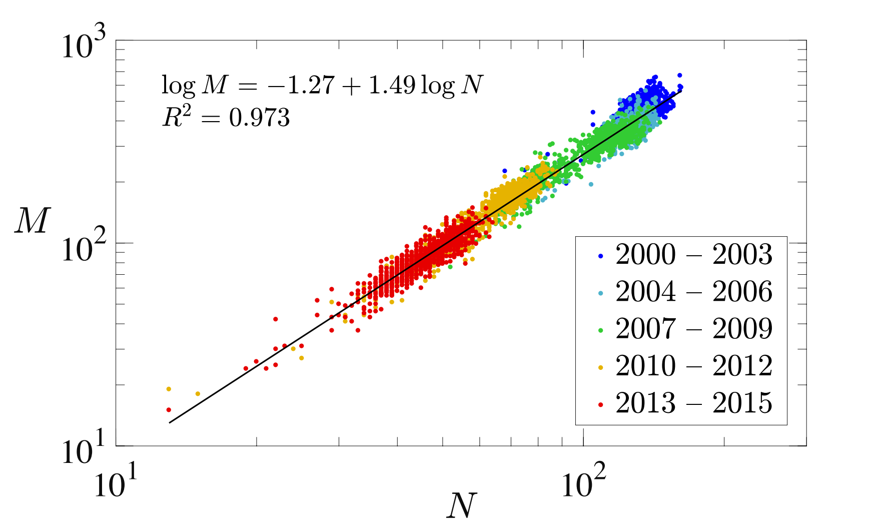
$$N_{\mathrm{p,ML}}(t) = \mathrm{argmax}_{N_\mathrm{p}} f(N_t, M_t|N_\mathrm{p})$$

Result: Estimation of market size

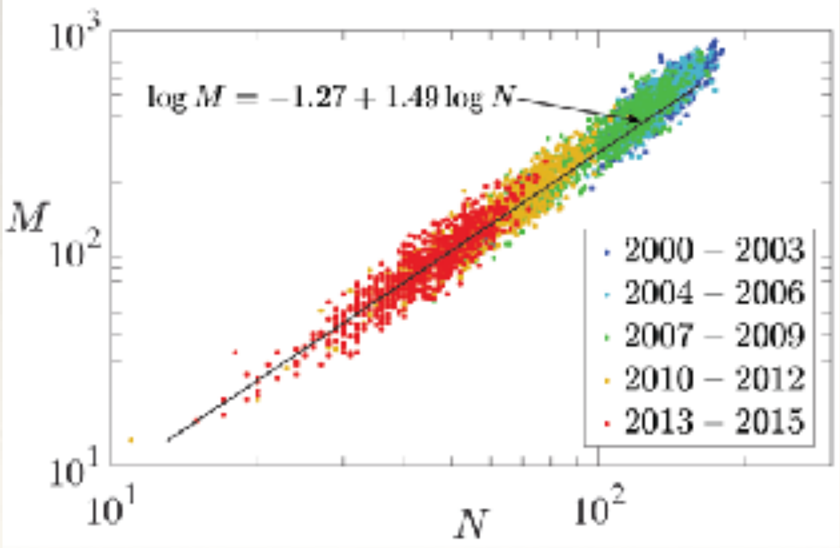
Daily estimates of N_p



data



model



Conclusion

Daily interbank networks have explicit patterns

- superlinear relation, power-law duration distribution

Banks are social creatures

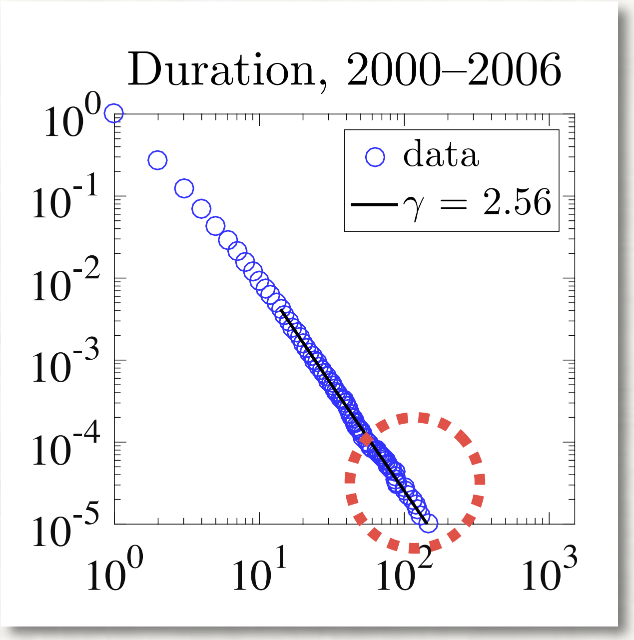
- Banks trade in the same way that people find conversation partners

Fitness model as a generative model of financial networks

- can explain many properties simultaneously
- contribute to systemic risk studies (Battiston et al. 2016, Science)

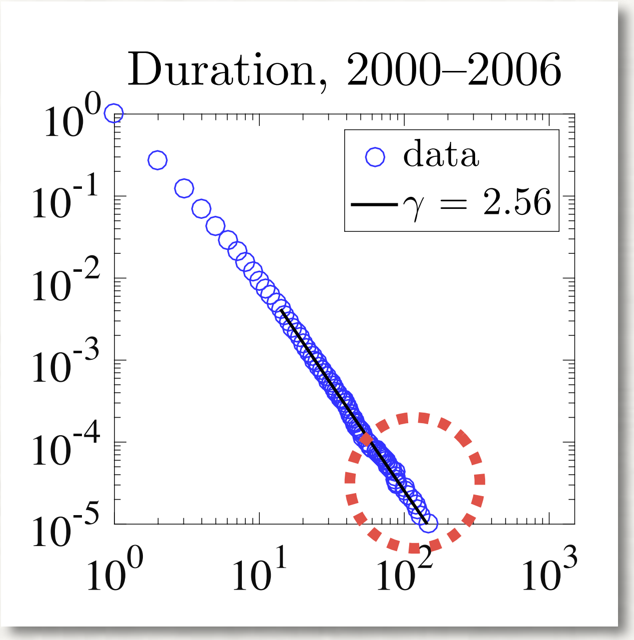
2. Extracting significant ties in temporal networks

Research question



- **Long duration for trades with particular pairs…**
- **Cannot happen if there are no preferences.**

Research question



- Long duration for trades with particular pairs…
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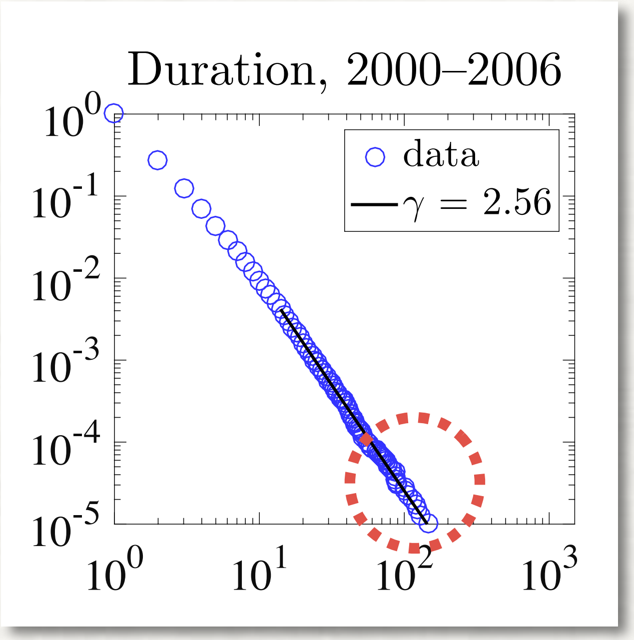
- How do banks choose trading partners?
- Could it be explained by random chance?

Research question



- Long duration for trades with particular pairs…
- Cannot happen if there are no preferences.

- How do banks choose trading partners?
- Could it be explained by random chance?

If not, "relationship lending!"

Relationship lending?

Commonly used measures

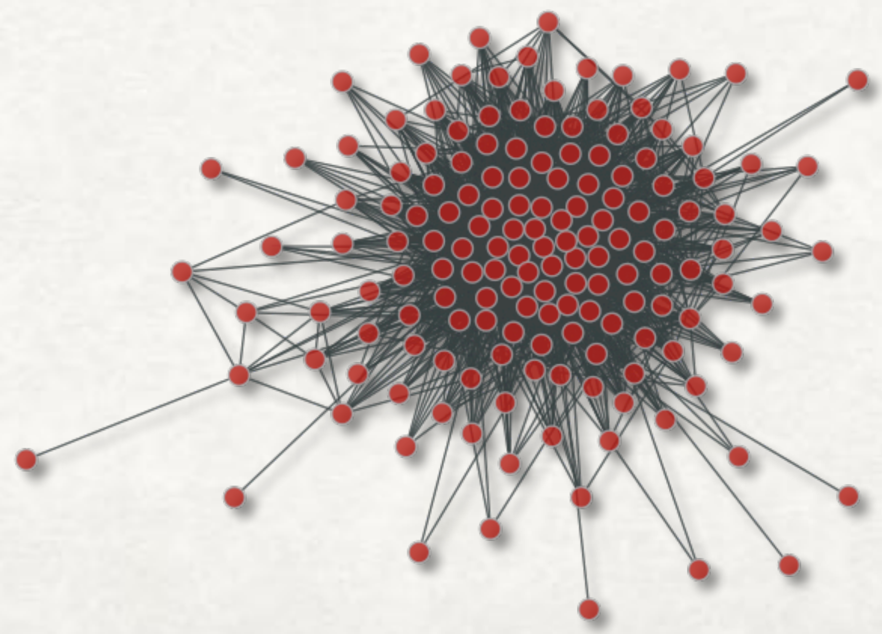
- # transactions between two banks
- Share of lending to a particular bank

…may be disturbed by

bank size, # total transactions, and market activity.

The aim of this work

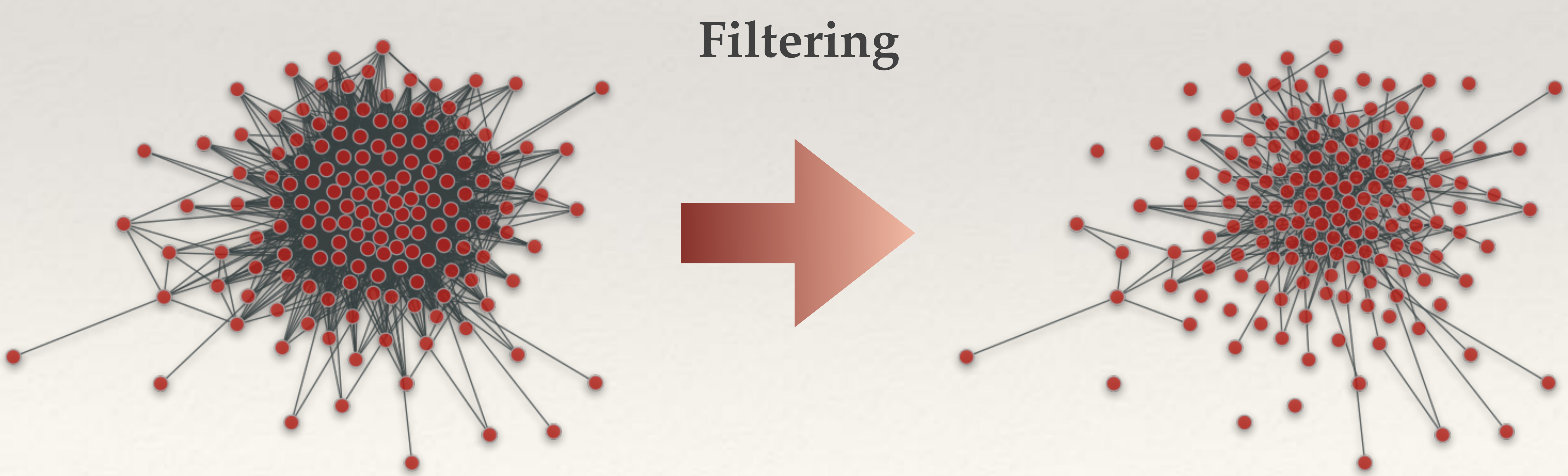
- Identify relationship lending in a statistically rigorous manner



Backboning

Extracting essential edges, i.e., "significant ties."

— The backbone of networks



Methods

Null model

"Fitness model"

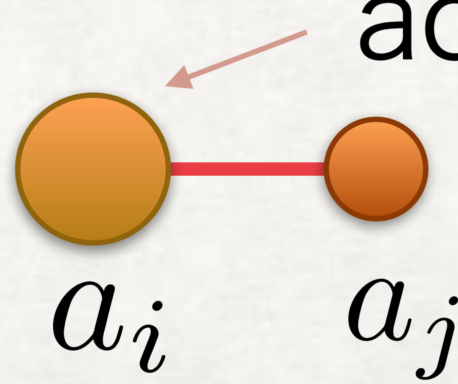
- Daily matching probability

$$u(a_i, a_j) = a_i a_j$$ Undirected

$$u_{i \to j}(a_i^{\text{out}}, a_j^{\text{in}}) = a_i^{\text{out}} a_j^{\text{in}}$$ Directed

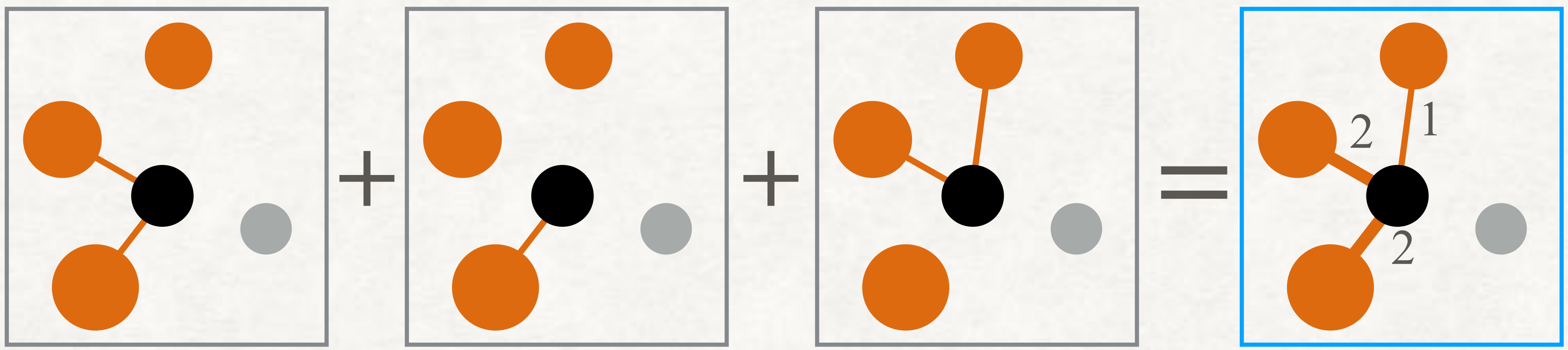
$$u(a_i, a_j, t) = a_i(t) a_j(t)$$ Time-varying

"activity" $\propto$ # trades

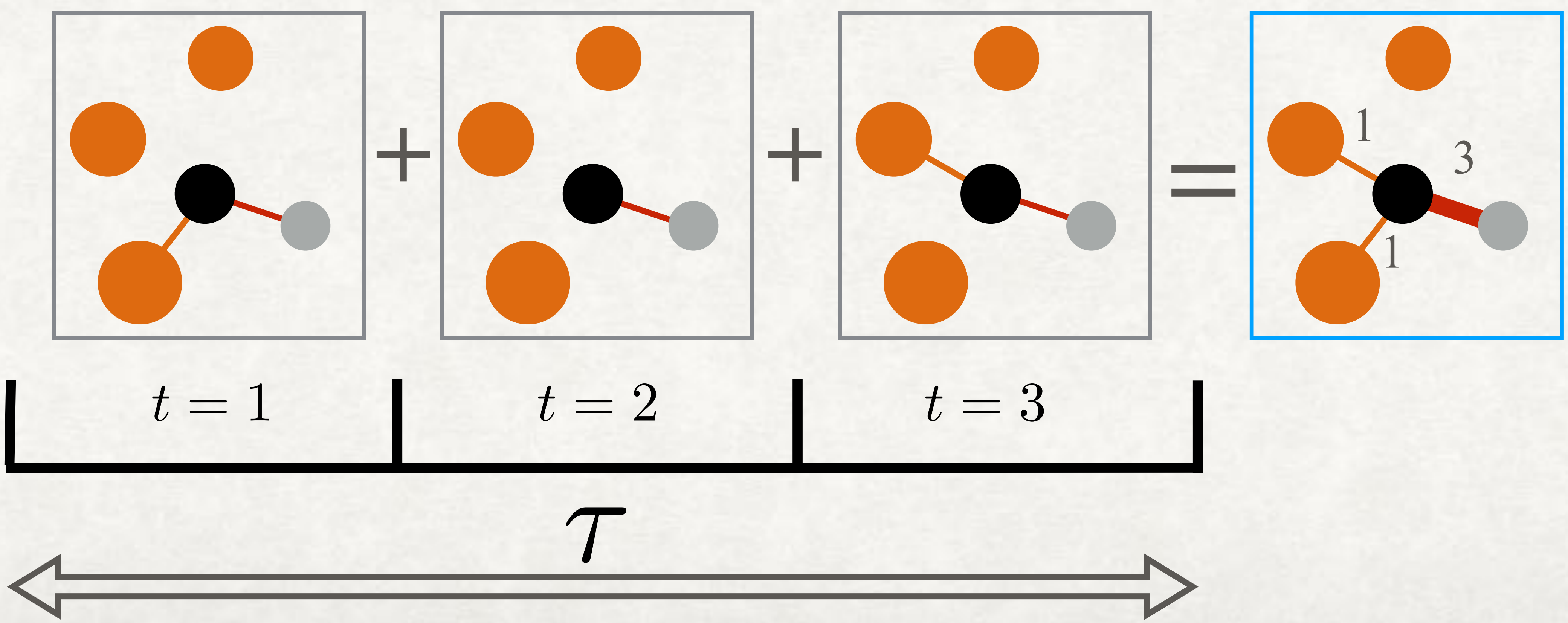


Sketch of our idea

Random matching (= Null hypothesis):



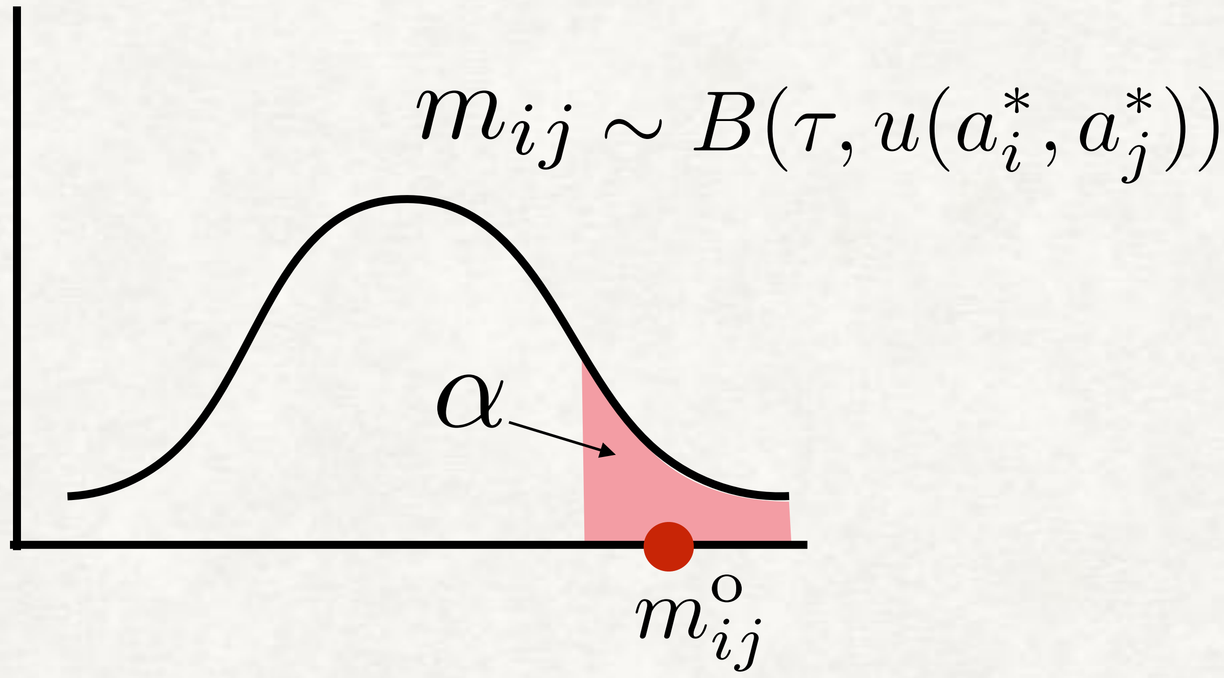
If there is a strong partnership:



Identification of significant ties

- **Edge-based test**

Under the null, m_{ij} follows a binomial distribution:



➡ Banks *i* and *j* are connected by a ***significant tie***.

Estimation of activity

Under random matching, # bilateral transactions should follow a binomial distribution:

$$p(\{m_{ij}\}|\vec{a}) = \prod_{i,j:i\neq j} \binom{\tau}{m_{ij}} u(a_i, a_j)^{m_{ij}} (1 - u(a_i, a_j))^{\tau - m_{ij}},$$

Estimation of activity

Under random matching, # bilateral transactions should follow a binomial distribution:

$$p(\{m_{ij}\}|\vec{a}) = \prod_{i,j:i\neq j} \binom{\tau}{m_{ij}} u(a_i, a_j)^{m_{ij}} (1 - u(a_i, a_j))^{\tau - m_{ij}},$$

ML estimator of activity:

$$F_i(\vec{a}^*) \equiv \sum_{j:j\neq i} \frac{m_{ij} - \tau(a_i^* a_j^*)}{1 - (a_i^* a_j^*)} = 0, \ \forall\, i = 1, \ldots, N,$$

Node-based test

Under the null, aggregate degree K_i follows a Poisson binomial distribution, approximated as:

$$f(K_i|a^*) \approx \frac{\lambda_i^{K_i} e^{\lambda_i}}{K_i!}$$

where $\lambda_i \equiv \sum_{j:j \neq i} [1 - (1 - u(a_i, a_j))^\tau]$

➡ $K_i < K_i^{\mathrm{C}}$ indicates bank i is ***relationship-dependent***.

Results

Tests on synthetic temporal networks

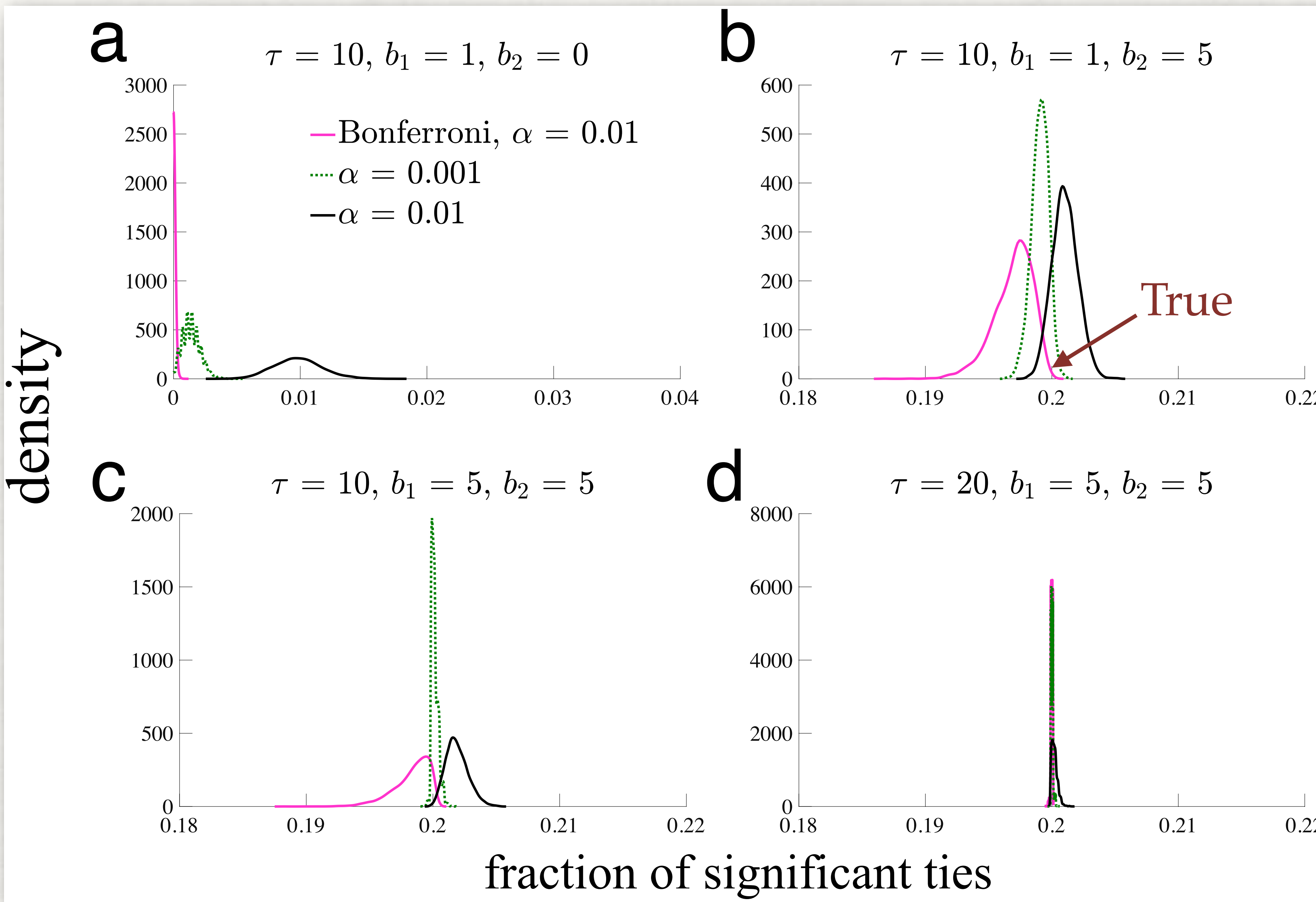
- Introduce “relationship lending”

1. Create random temporal networks
2. Assign a fraction of pairs as relationship pairs
3. Decreasing hazard prob for terminating a relationship:

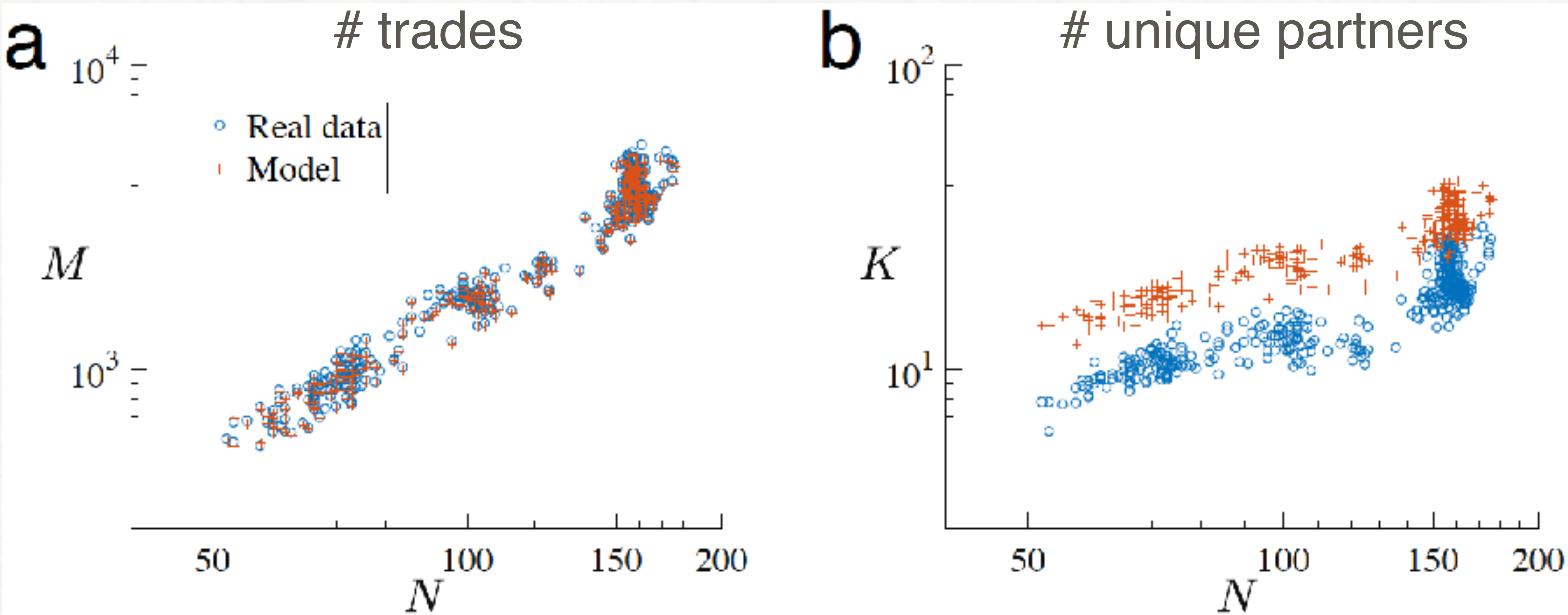
$$p_{ij}^{\mathrm{norel}}(t) = \frac{b_0}{b_1 + b_2 D_{ij}(t-1)},$$

Tests on synthetic temporal networks

True fraction = 0.2



Model fit

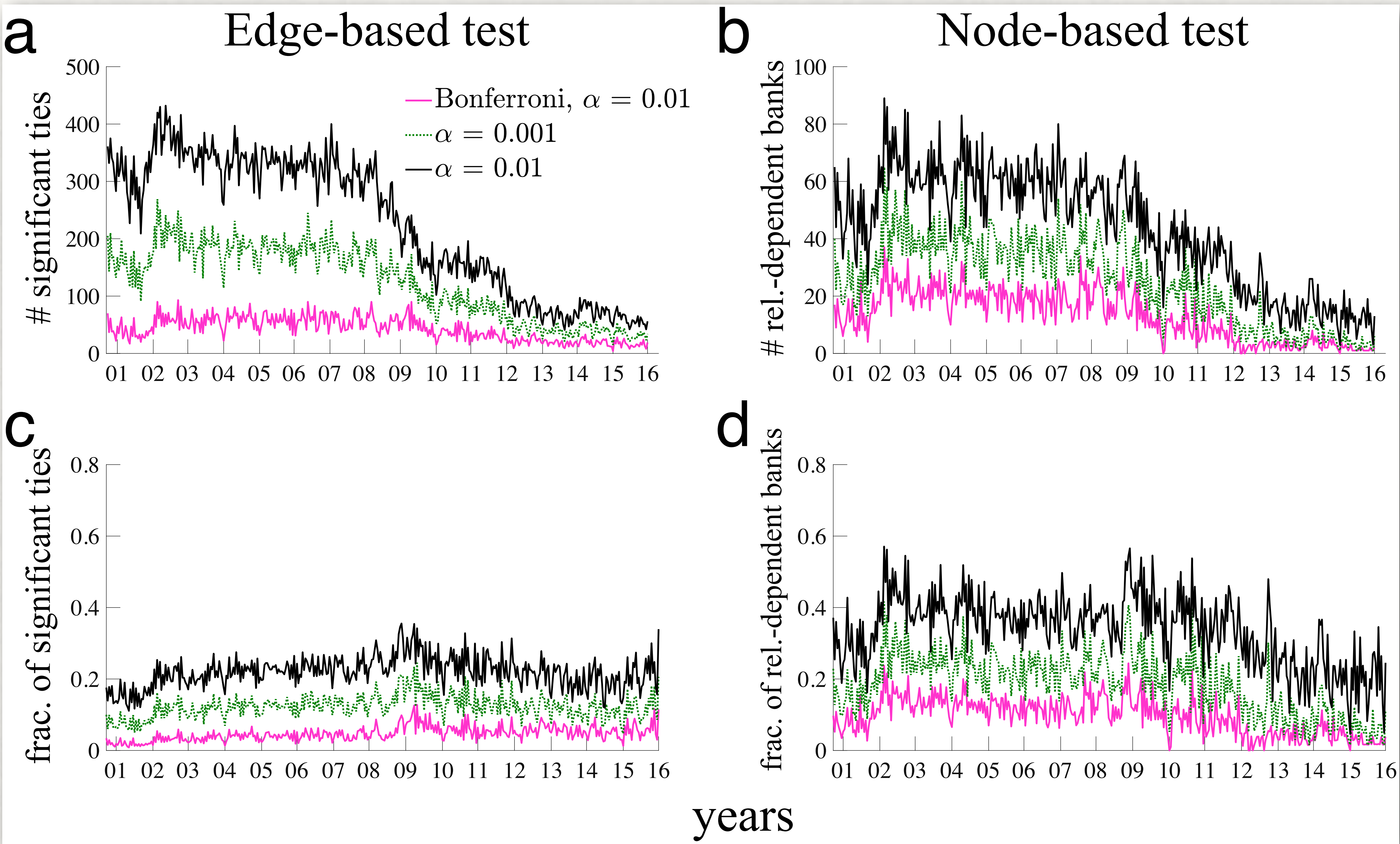


trades: real ≈ model
unique partners: real < model

→ Relationship lending?

Identification of significant ties

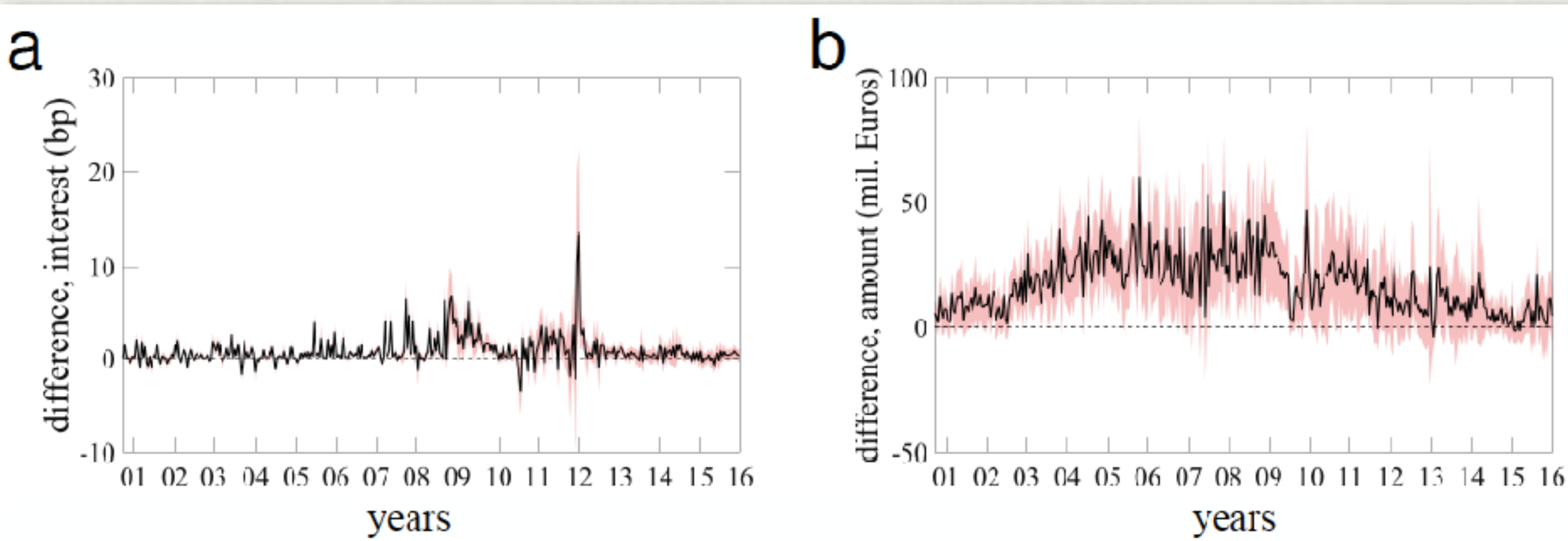
- **Undirected edge**



Impacts on trade conditions

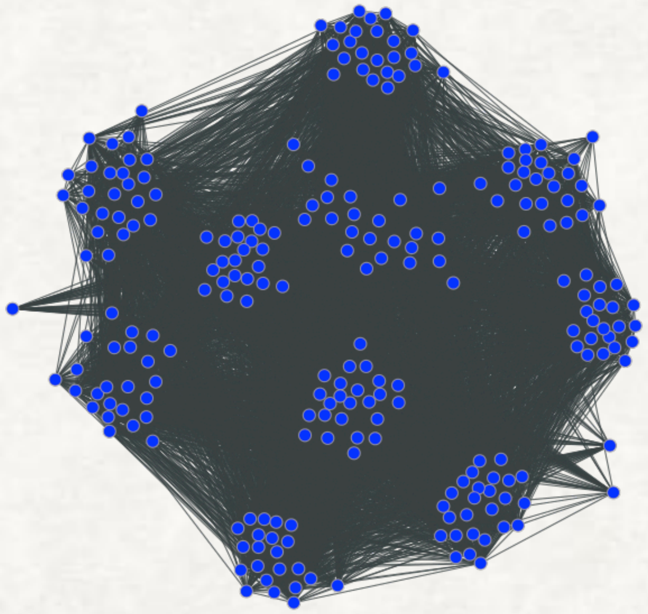
Difference in interest rates

Difference in trade amount



(relationship - non-relationship)

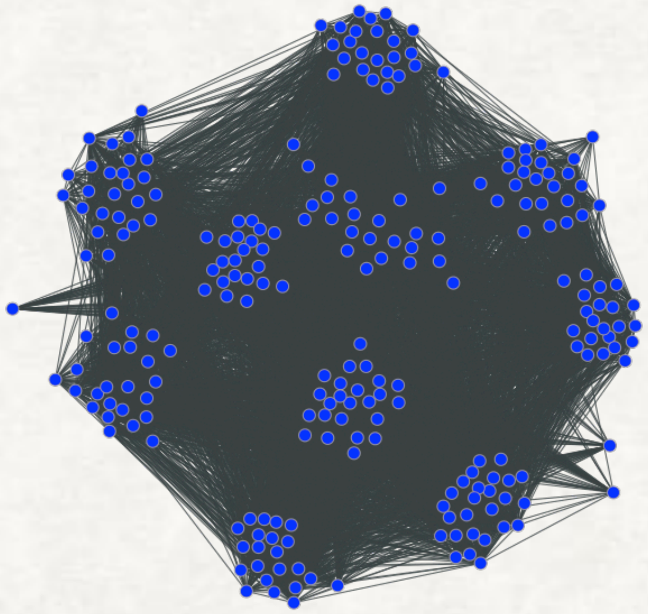
Application to face-to-face networks

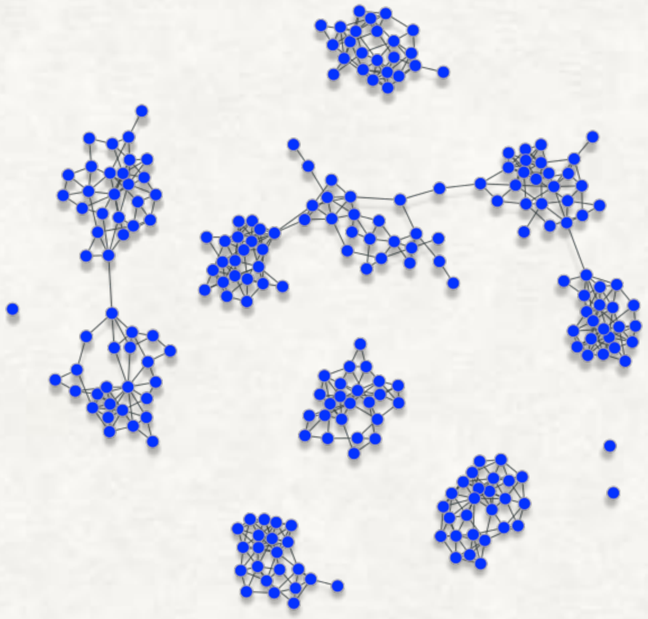


Nodes: High school students

Edges: Contacts

Application to face-to-face networks





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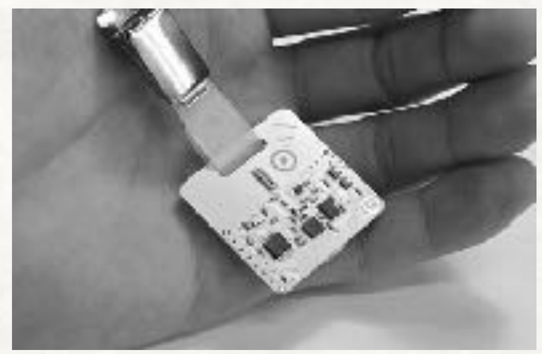
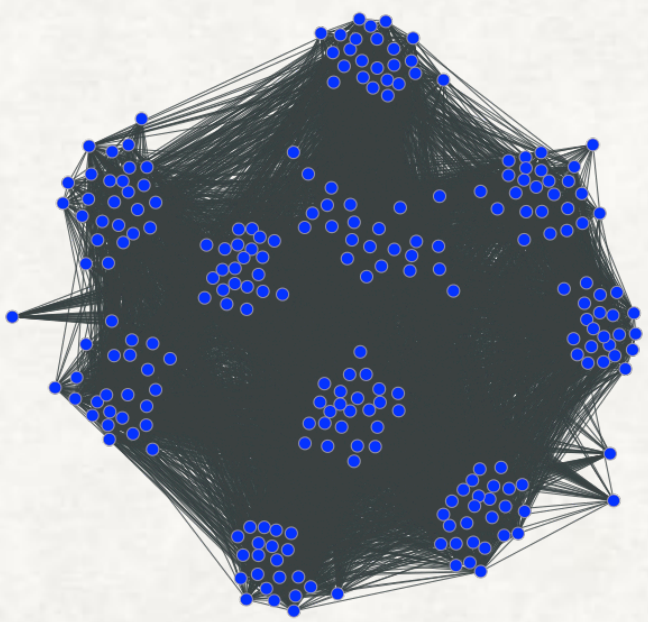
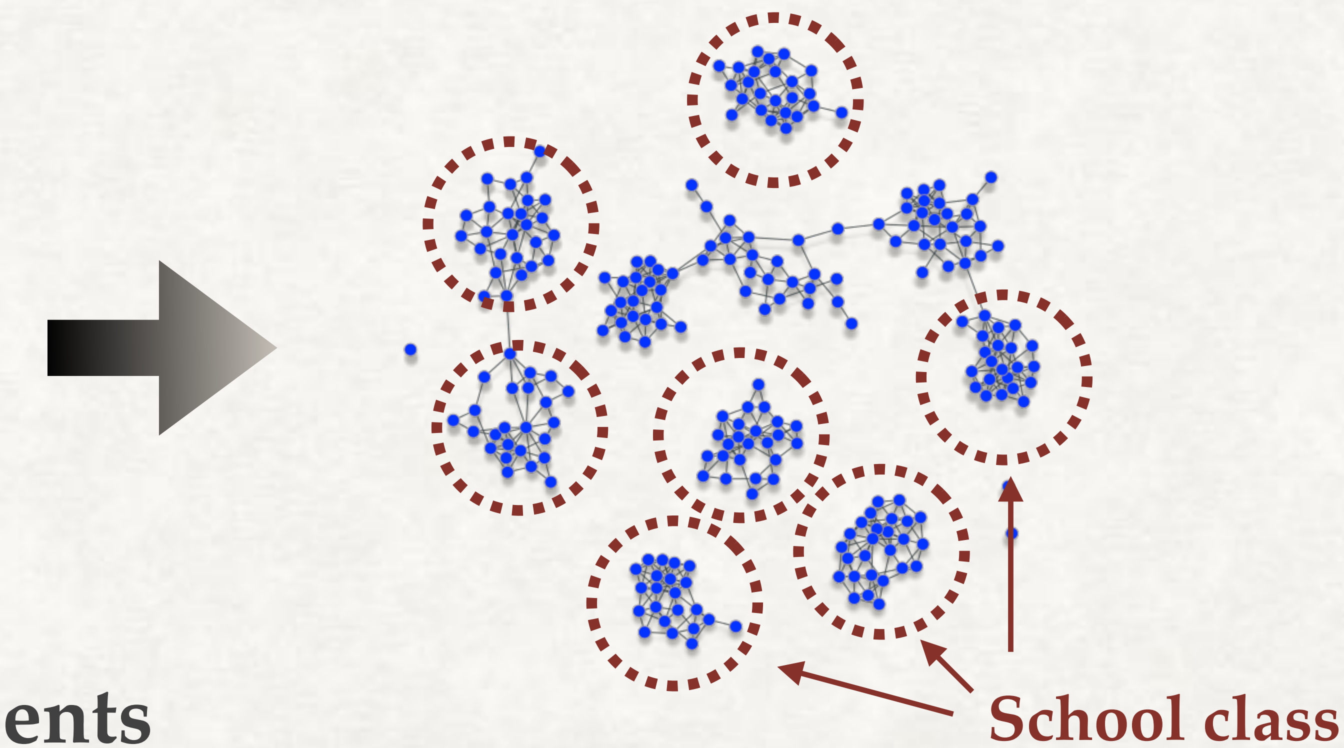






Nodes: High school students

Edges: Contacts

Conclusion

1. Significant ties and relationship-dependent banks are identified in a statistically rigorous manner.
2. Fraction of significant ties increased during the GFC.
3. The filtering method is also applicable to social networks.

JER: CALL FOR PAPERS

JAPANESE ECONOMIC ASSOCIATION

Call for papers for the *Japanese Economic Review* special issue: Economics and Complex Networks

Guest editors: Teruyoshi Kobayashi (Kobe University) and Naoki Masuda (University of Bristol)

Since the late 1990s, network analysis has been playing an increasingly important role in various fields of social sciences, natural sciences, engineering, and industry among others. This new research field, collectively called network science, has been benefiting from interdisciplinary research efforts and a growing quantity and variety of network data.

Submission deadline: May 31, 2020

Papers

"Social dynamics of financial networks",
T. Kobayashi, Taro Takaguchi, *EPJ Data Science*, 2018.

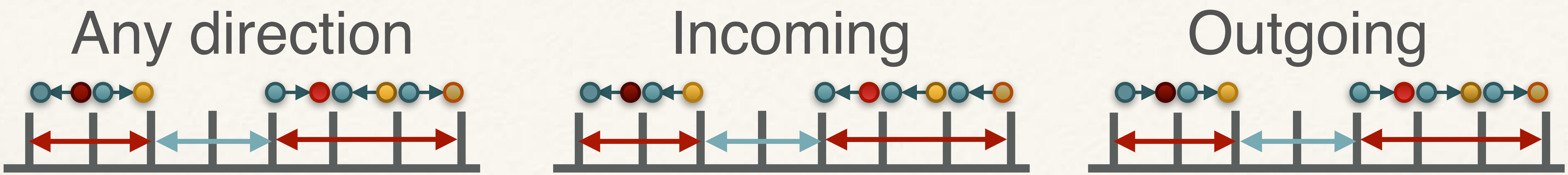
"Identifying relationship lending in the interbank market: A network approach",
T. Kobayashi, Taro Takaguchi, *J. Bank. Finance*, 2018.

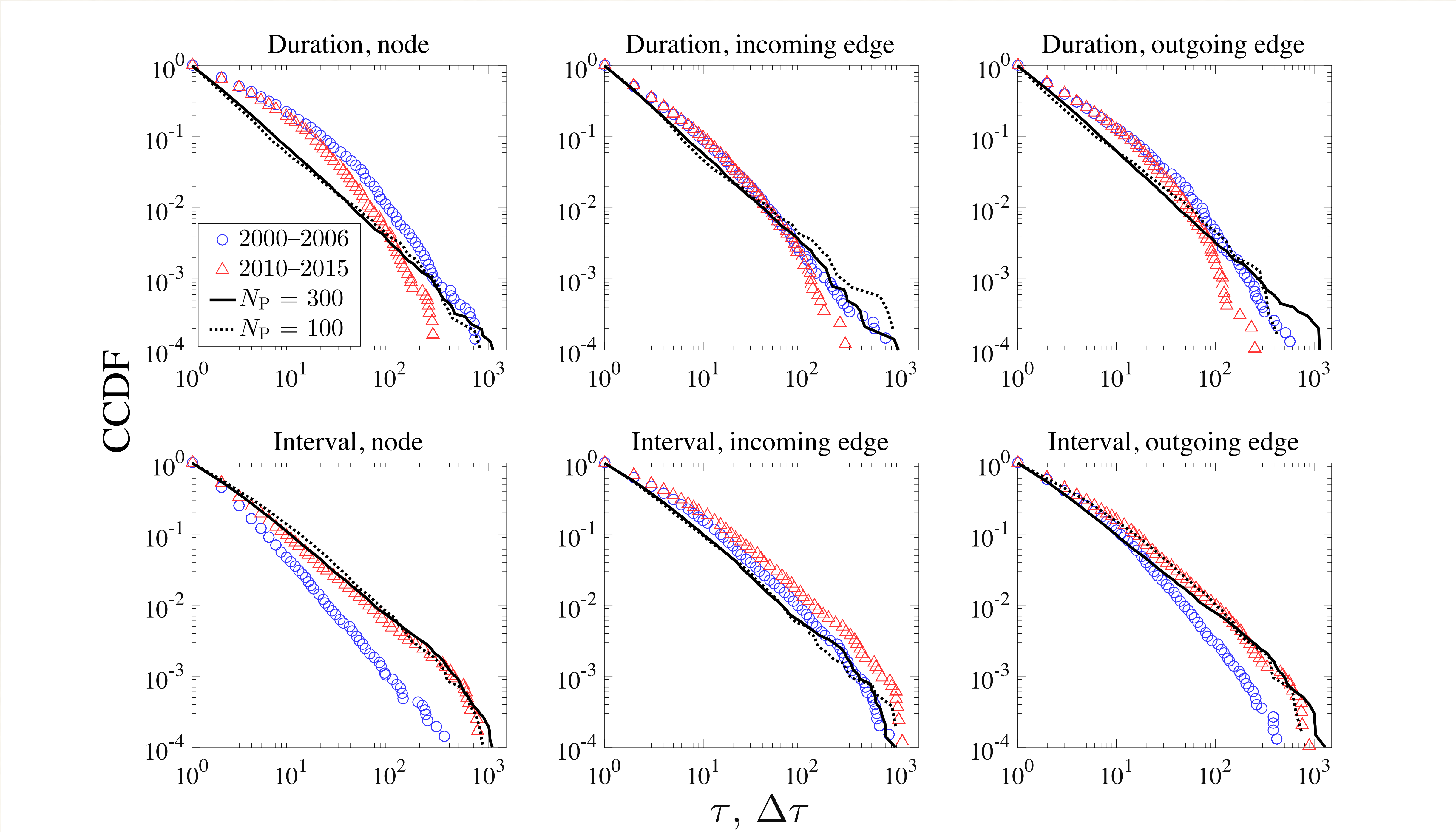
"The structured backbone of temporal social ties",
T. Kobayashi, Taro Takaguchi, A. Barrat,
Nature Communications, 2019.

Review article

"Network models of financial systemic risk: A review",
Journal of Computational Social Science 1, 2018,
Fabio Caccioli, Paolo Barucca, T. Kobayashi,

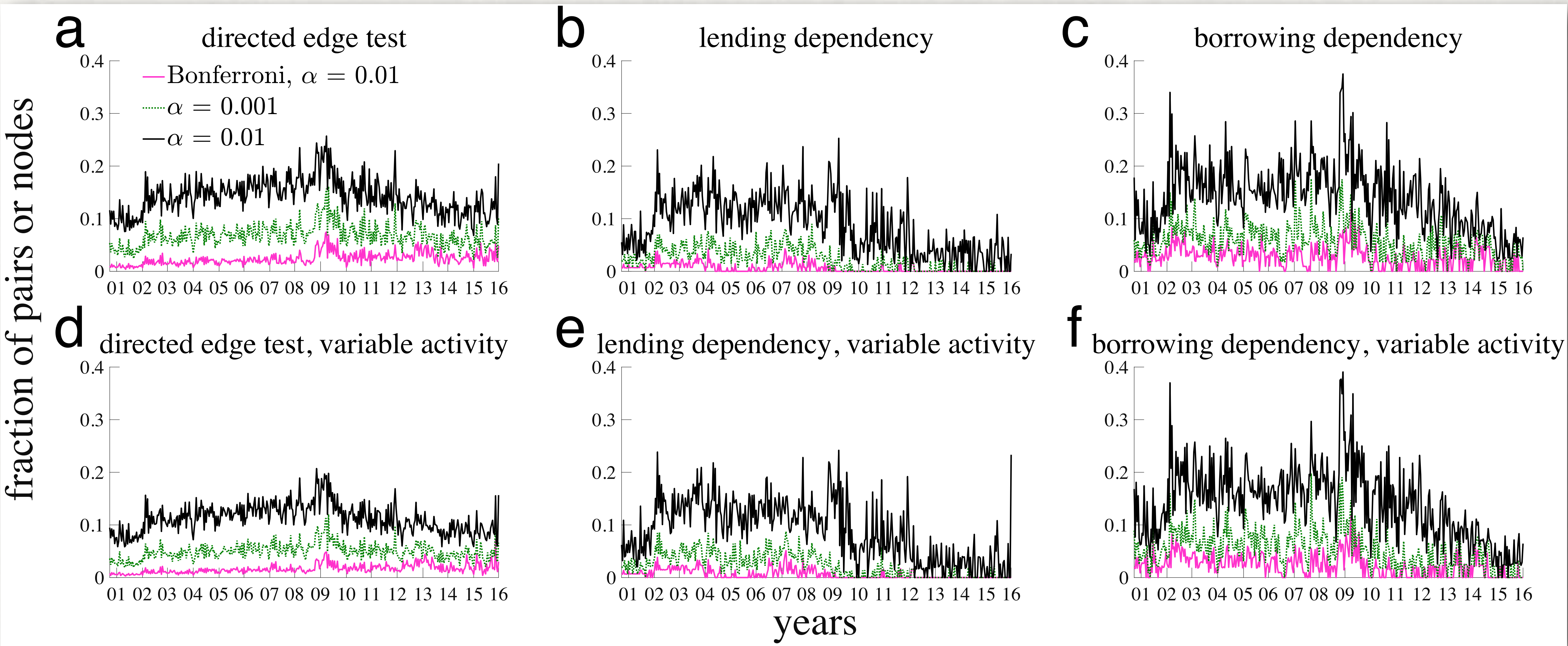
Duration and interval time (for nodes)





Identification of significant ties

- **Directed edge**



Previous research (excl. Econ)

- **Theoretical analysis of default cascades in financial networks** (EPJB 2013, PRE 2015)
- **Detection of important nodes in networks with community structure** (Sci. Rep. 2016)
- **Data analysis of interbank markets** (EPJ Data Science 2018)
- **Extraction of intra- and inter-day trading patterns of banks** (Sci. Rep. 2018)
- **Identification of "relationship lending" in the interbank market** (JBF 2018)
- **Backbone of temporal networks** (Nat. Commun. 2019)