Relational Theory and Models for Financial Networks

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12/13/2014

This work was partially supported by US National Science Foundation Grant SES-1357606 (to B.D.) and by US National Science Foundation Grant CISE-1320219 (to B.D.).
The Relational Structure of Finance

- **Contagion** – Who will be affected by the collapse of a bank or a major loan default?

- **Systemic Risk** – Some structures are more prone to contagion.

- **Market Power** – Some firms occupy a *privileged* position.

- **Politics** – Co-Ownership.

- **Financialization** – Deeper connectivity?
More Than the Sum of its Parts

Efficiency

Fault Tolerance
Plan for the Talk

- Relational Theory for Financial Networks
- Statistical Models for Network Structure and Dynamics
- Applications to Financial Networks
- Data Challenges and Future Directions
The Network

Nodes and Edges
Transitivity and Reciprocity

Transitivity – Clustering

Reciprocity – Collaboration, Stability
Preferential Attachment

Popularity – Power, Path Dependence

Sociality – Economies of Scale
## Data Format – Sociomatrix

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**Sender**
Statistical Models for Network Structure and Dynamics
The Exponential Random Graph Model

- Let $Y$ be a $n$-vertex network
- An ERGM is specified as:

$$P(Y, \theta) = \frac{\exp\{\theta' h(Y)\}}{\sum_{\text{all } Y^* \in Y} \exp\{\theta' h(Y^*)\}}$$

- $\theta$ is a parameter vector
- $h(Y)$ is a vector of statistics on the network
- Object of inference: the probability of $Y$ among all possible permutations of $Y$ given the network statistics.
- Only defined for binary networks.
The Generalized ERGM

- Transform unbounded continuous edges onto the [0,1] interval.

- $\lambda_{ij}$ parameterizes the transformation to capture marginal features of $Y_{ij}$

- We write the GERGM PDF of $Y$ as

$$f_Y(Y, \theta, \Lambda) = \frac{\exp[\theta'h(G(Y, \Lambda))]}{\int_{[0,1]^m} \exp[\theta'h(Z)] \, dZ} \prod_{ij} g(Y_{ij}, \lambda_{ij})$$
Estimation

- Start with MPLE parameter estimates.
- Use Metropolis-Hastings or Gibbs sampling to update parameters.
  1. Simulate networks using current parameters.
  2. Optimize over parameters.
- When parameters converge, stop algorithm.
- Check for degeneracy and model fit.
Model Degeneracy

![Graph showing edge density vs \( \theta_2 \) with different values of \( \alpha \). The graph illustrates the relationship between edge density and \( \theta_2 \) for various \( \alpha \) values, with distinct lines for each value, indicating the model degeneracy.](image-url)
Assessing Model Convergence

2.3 Goodness of fit

As in section 1, we assess the goodness of fit as follows.

R> gof2 <- gof(model2, nsim = 25)
R> plot(gof2)
Applications to Financial Network Data
Beyond “Gravity” in International Trade


- Yearly data on international trade flows from the UN Commodity Trade Statistics Database (1980-2001)

- Use of ERGM (thresholding data) and GERGM leads to substantively different results.
GERGM Results

**Sociality – (Exporters)**

**Popularity – (Importers)**

**Reciprocity**

**Transitivity**
Structure of International Lending


- Authors suggest this network is highly hierarchical. Our analysis draws this into question.
International Lending Network – 2005

Raw

Logged
Edge Transformation For Heavy-Tailed Financial Data

Raw Edgeweights -- Median: 553.307
Number of zero edges (omitted): 595

Transformed Edgeweights -- Median: 0.502
Number of zero edges (omitted): 619

Log data and normalize by maximum.
Observed 2005 Network vs. Random Network

- out2stars
- in2stars
- ctriads
- recip
- ttriads
- edgeweight

Box plots showing the distribution of network metrics for observed and random networks.
Model Specification – 2005 BIS Data

- Net $\sim$ Popularity + Sociality + Transitivity

- Hypotheses
  - Popularity (+) a few major borrowers.
  - Sociality (?) a few major lenders?
  - Transitivity (+) financial clustering.

- Because data are normalized ($\mu \approx 0.5$), do not need intercept.
Preliminary Results

Significant Transitivity, Anti-Popularity

![Box plots showing distribution of network metrics](image)
Data Challenges and Future Directions
Data Challenges

- **Dealogic LoanAnalytics**: $12,000/yr – all syndicated loans since 1980.

- **BVD Bank Scope**: $25,000/yr – Ballance sheet data back to 2000.

- **FedWire** – Need government collaborator, 100M+ large inter-bank transfers.

- **Tri-Party Repo** – NY Fed has the data, need to get access.
Future Directions

- **More Theory**: Unique features of financial networks?

- **R Package**: GERGM estimation implementation in `xergm` package

- **Applications** – systemic risk, 2008 financial crisis.