# Network models in FINancial TECHnology

Paolo Giudici and Branka Hadji Misheva

Fintech Laboratory and Phd
Department of Economics and of Computer Engineering, University of Pavia
E-mail: giudici@unipv.it; Facebook: Fintech Network

# Backgound

- FinTechs that make use of big data analytics, artificial intelligence and blockchain technologies bring new opportunities for banks, insurances and asset managers, as they improve user experience and reduce user costs;
- Fintechs can also reduce costs and improve revenues of incumbent financial companies;
- Fintechs increae interconnectedness between users, thereby further increase risks: credit risk (e.g. lendingtech), market risk (e.g. wealthtech) and cyber/fraud risks (e.g. paytech).

# Our contribution

Measure fintech risks to balance opportunities with risks.

1. Model peer-to-peer transactions to improve predictive accuracy of credit risk models;
2. Model asset correlations to improve classification and risk profile matching;
3. Model crypto asset prices and volumes to reduce market risks and detect anomalies;
4. Model Telegram and social network chats to predict fraudolent Initial Coin Offerings.

# Credit Scoring Models

- The most widely used model for building and estimating the probability of default is the logistic regression

$$ln(\frac{p_i}{1-p_i}) = \alpha + \sum_j \beta_j x_{ij},$$

from which:

$$p_i = \frac{1}{1+e^{\alpha+\sum_j \beta_j x_{ij}}}$$

# Correlation networks

- Companies are related by their past financial behaviour. These relationships can be embedded in a correlation network.
- If each company is a node in the network and we associate different time series with different nodes of the network, each pair of nodes can be connected by an edge with a weight equal to the correlation coefficient:

$$w_{xy} = \frac{T(\sum_t x_t y_t) - (\sum_t x_t)(\sum_t y_t)}{\sqrt{[T\sum_t x_t^2 - (\sum_t x_t)^2][T\sum_t y_t - (\sum_t x_t)^2)]}}$$

# Network-based scoring models

- We propose to extend scoring models including network centrality components, $g_i$:

$$ln(\frac{p_i}{1-p_i}) = \alpha + \sum_j \beta_j x_{ij} + \sum_i \gamma g_i$$

- from which:

$$p_i = \frac{1}{1+e^{\alpha+\sum_j \beta_j x_{ij}+\gamma g_i}}$$

# Results on SME lending - I

Figure: Correlation network based on the activity indicator

# Results on SME lending - II

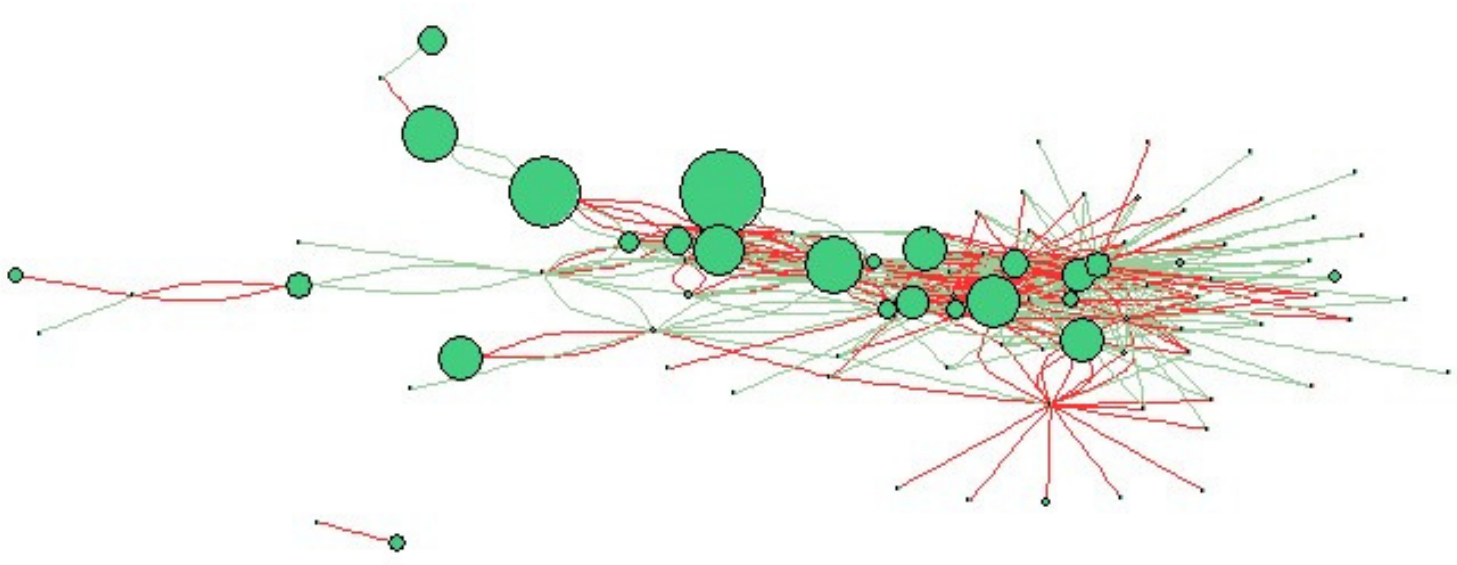

Figure: Correlation network based on the solvency indicator

# Predictive results on SME lending - base model

| Variable | Estimate | P-value | Significance |
|---|---|---|---|
| Intercept | -3.39 | 0.011 | * |
| Solvency ratio | 0.01 | 0.539 | |
| Debt to equity ratio | -0.07 | 0.517 | |
| Current ratio | 0.21 | 0.032 | * |
| Cash over total assets | -2.51 | 0.579 | |
| Return on equity | -0.08 | 0.008 | ** |
| Return on assets | 0.01 | 0.963 | |
| Return on Capital Employed | 0.09 | 0.044 | * |
| Coverage | -0.01 | 0.875 | |
| Activity ratio | -1.92 | 0.001 | *** |
| Predictive accuracy (AUROC) | | | **0.71** |

# Predictive results on SME lending - network model

| Variable | Estimate | P-value | Significance |
|---|---|---|---|
| Intercept | -1.53 | 0.033 | * |
| Solvency ratio | -0.02 | 0.012 | * |
| Debt to equity ratio | -0.00 | 0.576 | |
| Current ratio | 0.24 | 0.072 | * |
| Cash over total assets | 1.08 | 0.443 | |
| Return on equity | -0.11 | 0.000 | *** |
| Return on assets | 0.02 | 0.876 | |
| Return on capital employed | 0.01 | 0.212 | |
| Coverage | 0.02 | 0.248 | |
| Degree Centrality | 0.01 | 0.026 | * |
| Closeness | 1.05 | 0.002 | ** |
| Predictive accuracy (AUROC) | | | **0.82** |

# Summary findings - SME lending

- Network models can improve default predictions: in our results AUROC has increased from 0.71 to 0.82. In addition, they provide useful descriptive information that can be used to monitor companies that may trigger and spread contagion.
- We expect that further network information (e.g. transactional networks) can further improve model performance.

# Summary findings - BIS

| | Market Cds | Multivariate Borrowing | Multivariate Lending |
|---|---|---|---|
| GR | 0.0373 | 0.1120 | 0.1119 |
| PT | 0.0030 | 0.0092 | 0.0091 |
| IT | 0.0016 | 0.0064 | 0.0062 |
| ES | 0.0017 | 0.0064 | 0.0066 |
| IE | 0.0025 | 0.0081 | 0.0080 |
| US | 0.0006 | 0.0080 | 0.0051 |
| GB | 0.0006 | 0.0060 | 0.0060 |
| FR | 0.0007 | 0.0044 | 0.0058 |
| JP | 0.0006 | 0.0026 | 0.0038 |
| DE | 0.0005 | 0.0042 | 0.0050 |

Table: Mean CDS spreads: market standard and modified by capital borrowing effects (Multivariate Borrowing) and capital lending effects (Multivariate Lending)

# Results on cyrptoassets trade - I

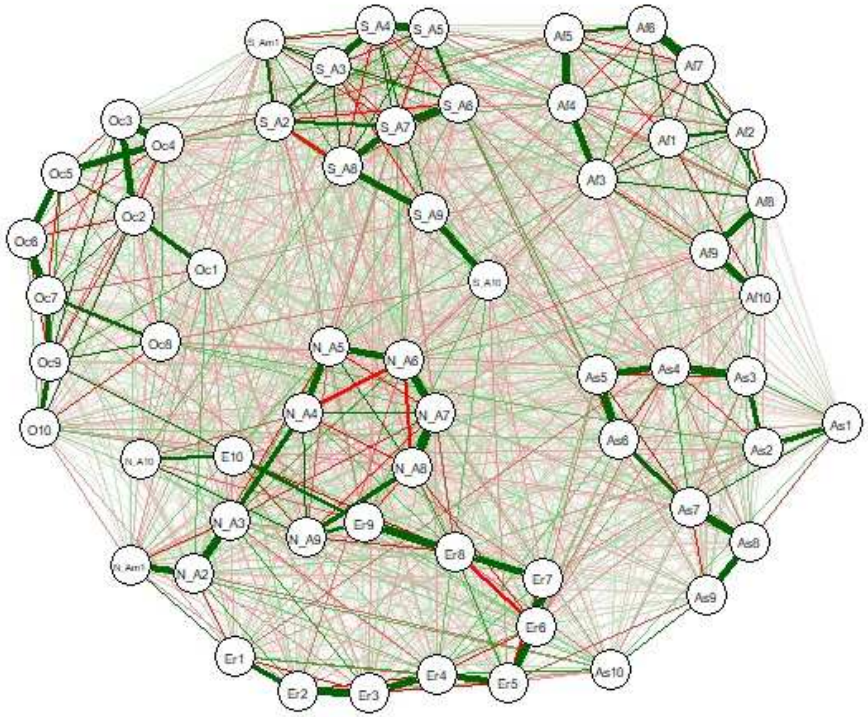


Figure: Partial correlation network obtained from bitcoin daily transaction volumes, in different geographical regions

# Results on cryptoassets trade - II

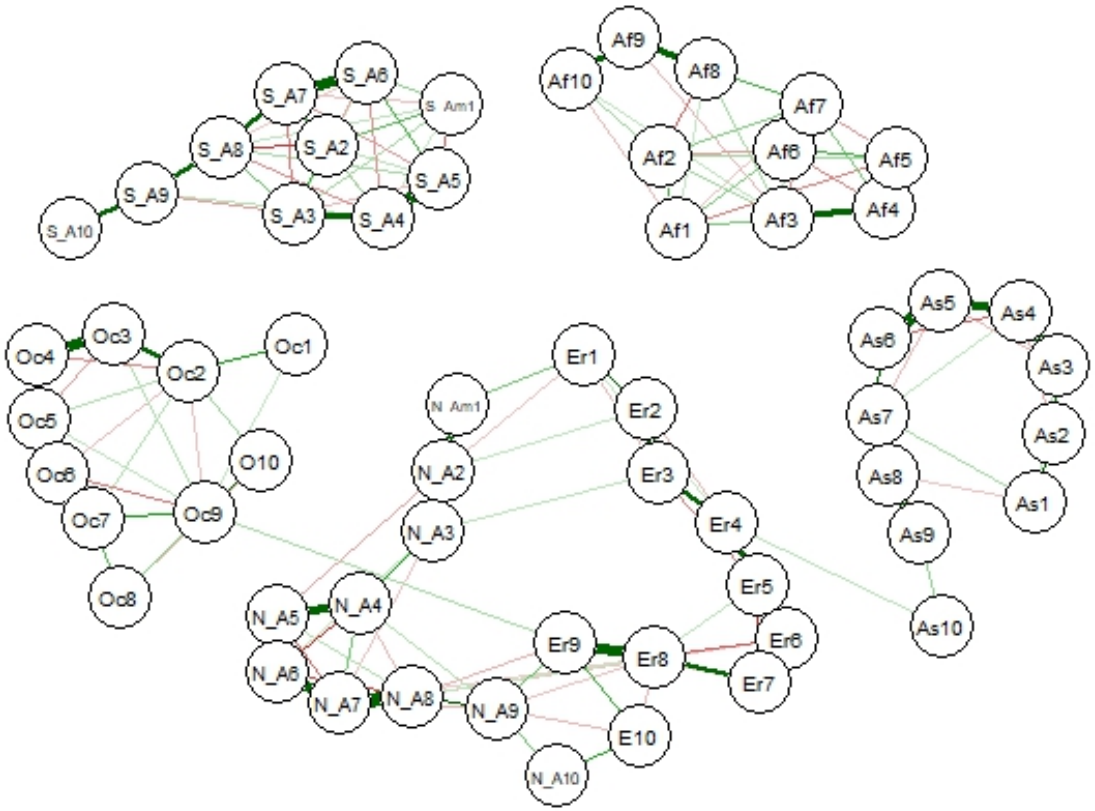


Figure: Partial correlation network obtained from bitcoin daily transaction volumes, in different geographical regions, regularised at $\alpha = 5\%$