Network models for credit risk management in peer to peer lending

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FinTech risk management

- FINancial TECHnology combines financial services with on-line and data driven innovative technologies.
- Advances in data science have enabled Fintechs to provide **competitive** financial services. They may bring, however, higher risks, e.g. **credit risk**, **cyber risk**, **compliance risk** and **market risk**. All amplified by **systemic risk**, due to the high interconnectdness between Fintech customers.
- Our aim is to develop network models for fintech risk management, that can measure and mitigate such risks, arising from **big data analytics**, artificial intelligence and blockchain technologies, and their applications to **peer-to-peer lending**, robot advisory and crypto assets.

Peer to peer Lending

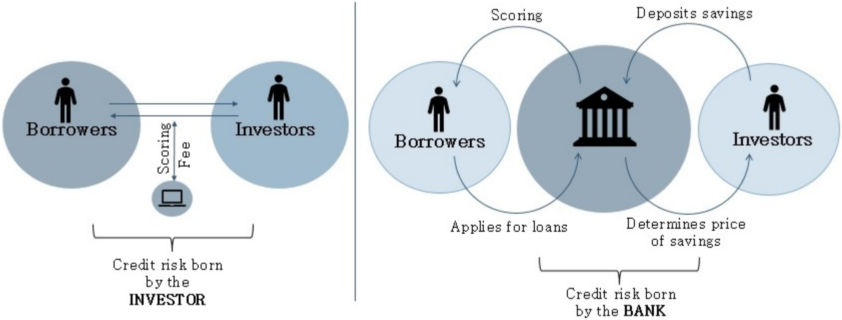


Figure: The business models of a P2P lender (left) and of a bank (right)

Peer to peer lending: our contribution

- Build a framework to test the predictive performance of scoring models employed by P2P platforms.
- Investigate whether peer-to-peer network information can improve predictive performance of credit risk models.
- So far we have analysed data from Lending Club (individuals) and modeFinance (SMEs)

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

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

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:

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

Descriptive results on SME data - I

Figure: Correlation network based on the activity indicator

Descriptive results on SME data - II

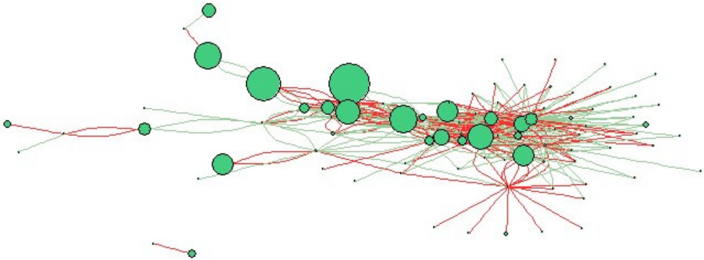


Figure: Correlation network based on the solvency indicator

Predictive results on SME data - Basic 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 data - 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**

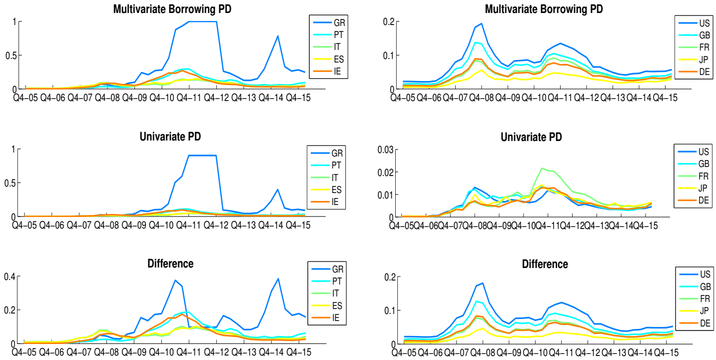
Main findings

- 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.

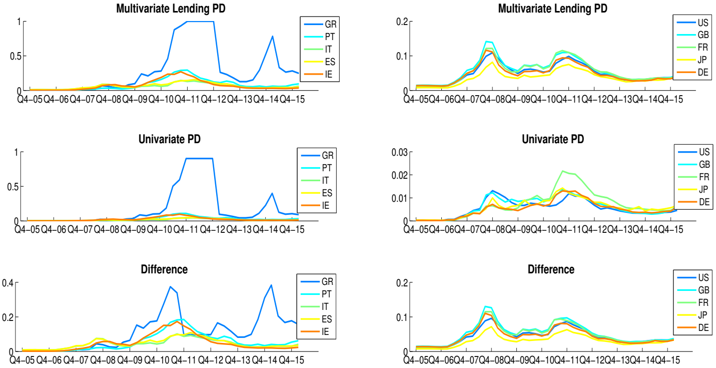
Research experience

- Paolo Giudici, Branka Hadji Misheva. Scoring models for P2P lending platforms: a network approach. Submitted to Journal of Banking and Finance.
- Paolo Giudici, Iman Abu-Hashish. What determines bitcoin exchange prices? A Network VAR approach. Submitted to Finance Research Letters.
- Stefan Avdjiev, Paolo Giudici, Alessandro Spelta. Measuring contagion risk in international banking. Submitted to Journal of Financial Stability
- (2017) Paolo Giudici, Laura Parisi. Sovereign risk in the Euro area: a multivariate stochastic process approach. **Quantitative Finance.**
- (2017) Pejman Abedifar, Paolo Giudici, Shatha Hashem. Heterogeneous market structure and systemic risk: evidence from dual banking systems. **Journal of Financial Stability.**
- (2017) Paola Cerchiello, Paolo Giudici, Giancarlo Nicola. Twitter data models for bank risk contagion. **Neurocomputing.**
- (2016) Paolo Giudici, Alessandro Spelta. Graphical network models for international financial flows. **Journal of Business and Economic Statistics**
- Paolo Giudici, Bihong Huang, Alessandro Spelta. Trade networks and economic fluctuations in Asia. Submitted to Journal of Money, Credit, Banking

BIS Project: capital borrowing effect on credit risk



BIS project: capital lending effect on credit risk



BIS project: summary of capital borrowing/lending effects

	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)