Latent Factor Models For Credit Scoring In P2P Systems

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Abstract

Peer-to-Peer (P2P) FinTech platforms allow cost reduction and service improvement in credit lending. However, these improvements may come at the price of a worse credit risk measurement, and this can hamper lenders and endanger the stability of a financial system. We approach the problem of credit risk for Peer-to-Peer (P2P) systems by presenting a latent factor-based classification technique to divide the population into major network communities in order to estimate a more efficient logistic model. Given a number of attributes that capture firm performances in a financial system, we adopt a latent position model which allow us to distinguish between communities of connected and not-connected firms based on the spatial position of the latent factors. We show through empirical illustration that incorporating the latent factor-based classification of firms is particularly suitable as it improves the predictive performance of P2P scoring models.

Keywords: Credit Risk, Factor models, Financial Technology, Peer-to-Peer, Scoring models, Spatial Clustering

1. Introduction

In the past ten years, the emergence of financial technology ventures ('FinTechs') in both the consumer and commercial credit space has introduced many opportunities for both lenders and investors, which has in turn redefined the role of traditional intermediaries. Since 2005, the growth of FinTech investments has been exponential, with their total funding jumping from around \$5.5B in 2005 to more than \$100.2B in 2017. A key development within the context of alternative financial service operators, is the emergence and fast growth of peer-to-peer lending platforms. The concept "peer-to-peer" captures the interaction between units while eliminating the need for a central intermediary. The origins of the term can be found in the field of computer networking where it describes a network where any one computer can act as a client or a server to other computers connected within the network without the need of connecting to a centralized server (Milne and Parboteeah, 2016).

In the context of finance, P2P platforms offer disintermediation by allowing borrowers and lenders to communicate directly. With the rapid growth of P2P lending activities, a key point of interest becomes assessing their risks, to protect investors and maintain financial stability. From a general viewpoint, despite the fact that P2P platforms offer many advantages

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to borrowers and lenders, causes for concerns do exist. Namely, P2P platforms are less able to deal with asymmetric information, compared to traditional banks. This can lead to adverse selection, in which investors cannot distinguish between borrowers belonging to different levels of credit risk. This problem is made worse by the difference in risk ownership that exists between P2P and traditional banking models. Although both banks and P2P platforms rely on scoring models for the purpose of estimating the probability of default of a loan, the incentive for model accuracy may differ significantly, as in the context of P2P lending platforms, in most cases, the credit risk is not born by the platform but, rather, by the investors. Because of P2P platform's inability to solve for asymmetric information as efficiently as traditional banks, and because of the differences in risk ownership, the scoring system of P2P lenders may not adequately reflect the "correct" probability of default of a loan.

A further issue associated with the nature of P2P platforms, not considered extensively within the literature, is that they are by construction globally-interconnected networks. This in turn suggests that the application of traditional scoring models may lead to bias and inaccurate classification of borrowers into different levels of credit risk. Specifically, classical banks have, over the years, segmented their reference markets into specific territorial areas, or into specific business activities, increasing the accuracy of their ratings but, on the other hand, increasing concentration risks. Differently, P2P platforms are based on a "universal" banking model, fully inclusive, without space and business type limitations, that benefits from diversification but which suffers from a difficult scoring mechanism.

We claim that the inclusion of network information can improve loan default predictions, as it captures information that reflects underlying common features, that cannot be otherwise observed. For related works see Wilson and Sharda (1994) and Letizia and Lillo (2018). Besides improving predictive accuracy, a network representation can also provide valuable "descriptive" insights on the interconnectedness between companies participating in the P2P platform, identifying participants which are central to the network and, therefore, most important from a systemic risk perspective. In line with this, our main contributions are two: i) to analyze the predictive performance of scoring models employed by P2P platforms, specifically in SME lending; ii) to investigate whether network-based scoring model can improve loan default predictions, and, therefore, better protect investors, and better preserve financial stability.

Network modeling has become increasingly recognized as a powerful methodology for investigating and capturing interactions between economic agents and among financial institutions (Ahelegbey et al., 2016a,b; Billio et al., 2012; Diebold and Yilmaz, 2014; Minoiu and Reyes, 2013). In particular, correlation network models, that rely on correlations matrices between the units of analysis (borrowers, in our context) for the purpose of deriving an adjacency matrix between them, have been proposed by Giudici and Spelta (2016), Giudici and Parisi (2017), Giudici et al. (2017) and Giudici and Parisi (2018). The use of correlation networks in financial studies has grown in popularity, because they provide a simple and useful tool for representing and visualizing the structure of pairwise cross correlations among a set of units, over a particular time period. This allows to obtain deeper insights into the mutual interconnections that exist between different statistical units, exactly as classical correlation analysis allows to understand the mutual relationships between different statistical variables. For related works on the application of correlation networks and centrality measures for risk quantification see Aste et al. (2005, 2010); Barfuss et al. (2016); Mantegna (1999); Massara et al. (2016); Musmeci et al. (2017); Pozzi et al. (2013); Tumminello et al. (2005).

In the context of peer to peer lending, we propose a network-based scoring models based on an alternative method of inferring links between P2P participants, based on uncovering community structures within them.

Most financial systems are characterized by the existence of structural modules that play significant roles and define the functional role of the system (Sarkar and Dong, 2011). Communities in a network are the dense group of nodes which are tightly coupled to each other within the group and loosely coupled to the rest of the nodes in the network (Khan and Niazi, 2017). Community detection within the context of P2P platforms will allow us to better understand the properties and functionalities of the network and also it will also help the process of developing and estimating a more efficient scoring model for these platforms which in turn will ensure higher-level protection for investors and overall financial stability.

By representing SMEs which have applied for a loan to a P2P lending platform as vectors in real space, expressed as linear combinations of orthogonal bases described by singular value decomposition (SVD), orthogonality becomes a metric for classifying the respective SMEs into communities. Specifically, the information contained in the eigenvectors and eigenvalues are at the center of all spectral graph partitioning approaches. In the context of this study, nodes are partitioned in two groups such that companies connected to each other belong to the same community. Once the adjacency matrix based on the SVD approach is inferred, we estimate and compare the predictive utility of traditional scoring models for connected and not-connected nodes independently. Note that, in applying this approach, we attempt to replicate the segmentation practices which are an imperative factor of bank's service offering and main determinant of the accuracy of their scoring models.

To summarize, this paper contributes to the literature on credit scoring for P2P lending by: a) propose a new network-based scoring model, that leverages the structure of network communities, obtained using all available information; and b) demonstrate that such a model improves predictive accuracy and, therefore, reliability, of credit risk estimations provided by P2P platforms. By increasing the ability of P2P lenders to successfully discriminate between different risk classes, the proposed methodology indirectly helps stabilize the overall financial system. Namely, although regulators are greatly interested in managing credit risk exposure, they cannot apply such models as they are based on commercial data made available only to the P2P lending platform.

The paper is organized as follows. Section 2 contains the proposed methodology, Section 3 discuss application to a credit scoring database provided by a European rating agency that supplies credit risk information to P2P platforms and, Section 4 presents concluding remarks.

2. Methodology

2.1. Scoring Models

Generally, the main linear statistical tool used for developing credit scoring model is the logistic regression. In the context of P2P lending, logistic regression has been used in the studies of Andreeva et al. (2007); Barrios et al. (2014); Emekter et al. (2015); Serrano-Cinca and Gutiérrez-Nieto (2016). This approach aims to classify the dependent variable in two groups, characterized by a different loan status [1=default; 0=no default] in which borrowers are classified by logistic regression, specified by the following model:

$$ln(\frac{p_i}{1-p_i}) = \alpha + \sum_{j=1}^{m} \beta_j x_{ij} \quad (1)$$

where p_i is the probability of default, for borrower i, $x_i = (x_{i1}, \ldots, x_{im})$ is an m dimensional vector of borrower-specific explanatory variables, and the intercept parameter α, as well as the regression coefficients β_j, for $j = 1, \ldots, m$, are to be estimated from the available data. It follows that the probability of default can be obtained as:

$$p_i = \left(1 + \exp(\alpha + \sum_{j=1}^{m} \beta_j x_{ij})\right)^{-1} \tag{2}$$

We remark that, in the case of low default frequencies, which can typically occur for highly "selective" P2P platforms, logistic regression could be replaced by other generalized linear models, such as the generalized extreme regression scoring model proposed by Calabrese and Giudici (2015). One approach for incorporating network information into the econometric specification is by extending the work of Chinazzi et al. (2013) by adding network summary measures to the logistic regression context. This leads to the proposal of a network-based scoring, which may take the following form:

$$ln(\frac{p_i}{1 - p_i}) = \alpha + \sum_{j} \beta_j x_{ij} + \gamma g_i \tag{3}$$

where p_i is the probability of default, for borrower i, $x_i = (x_{i1}, \ldots, x_{ij}, \ldots, x_{iJ})$ is a vector of borrower-specific explanatory variables, g_i is the network centrality measure for borrower i and the intercept parameter α and the regression coefficients γ and β_j, for $j = 1, \ldots, J$, are to be estimated from the available data. Specifically, what is suggested by Giudici and Hadji-Misheva (2017) is using correlation network models for deriving an adjacency matrix between the participants in the P2P platform. Once an adjacency matrix is derived, estimated centrality measures are incorporated into the predictive model.

However, the above specification suffer for one important limitation: it requires the preliminary choice of an explanatory variable, on which to derive the correlation matrix between the observed company times series. This may be fine when one variable is sufficient to discriminate credit behavior; when more variables, instead, are required, an alternative approach is necessary. To build correlation network models that simultaneously consider more variables, we propose a network-based scoring model that uncovers community structures within them. Communities in a network are the dense group of nodes which are tightly coupled to each other within the group and loosely coupled to the rest of the nodes in the network (Khan and Niazi, 2017).

Our approach can be described by three consecutive steps. We first obtain the latent factors (positions) for each credit applicant (i); we then infer communities between connected and not-connected nodes (ii); last, we estimate and compare the predictive performance of logistic regression models, separately for connected and not-connected nodes (iii). In the next two subsections we describe steps (i) and (ii), while (iii) is the logistic regression model described in this section, applied separately to each of the found communities.

2.2. Latent Factor Model

Let Z be an arbitrary $n \times m$ matrix. The singular value decomposition (SVD) of any $n \times m$ non-symmetric matrix Z can be expressed as

$$Z = UDV' \tag{4}$$

where $D = \Lambda^{1/2}$ is a diagonal matrix, with Λ interpreted as the diagonal matrix of nonzero eigenvalues of $Z'Z$ and ZZ', U and V are matrices whose columns are the orthonormal eigenvectors of ZZ' and $Z'Z$ respectively. More specifically, U is referred to as the matrix of the left singular vectors that span the column space of Z and the columns of V span its row space and are referred to as the right singular vectors.

Let $X = (x_1, \dots, x_n)'$ be a stacked collection of the institutional features. Following Hoff (2007), we relate the observations in X to the following model

$$X = Z + E = UDV' + E \tag{5}$$

where Z is the expectation of X and E is the errors assumed to be normally distributed with mean zero and covariance matrix Σ.

We assume the observed institutional attributes are driven by some unobserved underlying factors that signal the financial conditions of the institution. We consider a lower dimensional number of factors (i.e, $k < m$). Thus, following (5), we express each x_i as:

$$x_i = u_i DV' + \varepsilon_i = f_i V' + \varepsilon_i \tag{6}$$

where $u_i = (u_{i,1}, \dots, u_{i,k})'$ is a k dimensional vector representing the i-th row of U, D is a $k \times k$ diagonal matrix, V is the $m \times k$ matrix of factor loadings and $f_i = u_i D$ is the vector of factor scores.

2.3. Network inference

Following the literature on latent space models, we consider a class of network models commonly referred to as inner-product models (see Durante and Dunson, 2014; Hoff, 2008). In this framework, we project the latent factors onto a "social space" and nodes that are "close" to each other are more likely to be connected. Let A be an $n \times n$ binary adjacency matrix where $A_{ij} = A_{ji} = 1$ indicates a link between nodes i and j, and zero otherwise. We parameterize the ij-th entry of A via a probit mapping function given by

$$P(A_{ij} = 1 | f_i, f_j, \theta) = \pi_{ij} = \Phi(\theta + f_i' f_j) \tag{7}$$

where π_{ij} is the probability of a link between nodes i and j, Φ is the cumulative density function of the standard normal distribution, and θ is a constant. In estimating a network for a large number of nodes, a common approach is to approximate the network by a sparse structure. Following the literature on sparse graphical models, we set $\theta = \Phi^{-1}(\frac{2}{n-1})$. From (7), we define a link between nodes i and j by

$$A_{ij} = (\pi_{ij} > \pi_0) \tag{8}$$

Thus, node i is connected to node j if and only if the probability of a link between the two nodes exceeds π_0. The choice of the threshold π_0 may be put in correspondence with the proportions of the event of interest within the total sample.

3. Application

3.1. Data

To implement our proposed models, we consider data supplied by a European External Credit Assessment Institution (ECAI), that supplies credit scoring to P2P platforms focused

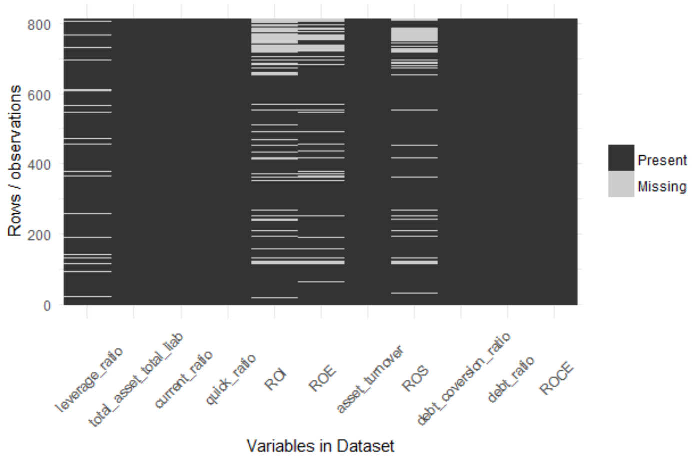


Figure 1: Histogram of missing data

on SME commercial lending. Specifically, the analysis relies on a dataset composed of official financial information (44 balance sheets and income statement variables) on 813 SMEs, mostly based in Southern Europe, for the year 2015. To make data consistent between different European countries, financial data has been reclassified to minimize the differences based on different fiscal legislations. The majority of the companies included in the sample are Italian based enterprises with less than 20 employees and strong focus on manufacturing. The proportion of observed defaults in the sample is equal to 13.8%, a large proportion, in line with the observed impact of the recent financial and debt crisis in Europe and, specifically, in Southern European countries.

3.1.1. Data Pre-Processing

As it is the case with most studies, when collecting balance sheet data on companies, the required count or value for some variables are not available. Although this is a problem that arise in most empirical research relying on financial and non-financial data about economic agents, very rarely do authors stray from the complete cases analysis. This approach can be problematic as it considered inefficient and possibly leading to bias conclusions (Briggs et al., 2003). In line with this, in this paper we adapt the imputation method for generating replacements values for missing data which in turn allows for the use of the full number of observations.

In the context of the dataset used in this paper, missing variables are present for four main variables indicating the leverage and profitability condition of the SMEs. Figure 1 provides the histogram of missing data. Looking at the histogram in Figure 1 we observe that the four variables for which most NAs are present are: (i) the leverage ratio, (ii) the return on investment ratio, (iii) the return on equity ratio and (iv) the return on sales ratio. These represent some of the most crucial financial ratios determining the companies' overall financial health which in turn impacts the probability of loan default.

The most used imputation methods take a set of complete predictors and returns a single imputation for each variable. In this paper we follow a multiple approach, in which imputations are created by repeated calls to the elementary imputation function. Considering that all four variables which contain NAs are continuous variables, the imputation method we employ is predictive mean matching Burton et al. (2007).

In the literature there has been an extensive discussion on when it is appropriate to use an imputation function rather than following the complete case approach. In most cases, the choice depends on two main elements: (i) whether the missing data mechanism is ignorable and (ii) whether the imputations contain information coming from outside the model used for predictions. In the context of this study, some negative implications from the use of the imputation function could arise. Specifically, the variance of the variables subjected to the imputation function may be reduced once the missing values are included which in turn could lead to bias estimates. However, we justify our choice by two main arguments. First, it is the view of the authors that the missing data mechanism is not ignorable as the variables with the highest NA count are crucial determinants of the probability of default hence the use of the complete case approach, could lead to bias estimates. Second, the imputations are based on information from outside the model which are relevant to the outcome and at the same time are not predicted by the other covariates. Table 1 present a description and summary statistics of the variables in our sample.

3.2. Descriptive Modeling

The purpose of this subsection is to elaborate on the community formation identified in the context of SME-focused P2P lending platforms and investigate the systemic importance of SMEs and their potential influence on other companies within the network.

Following (Bai and Ng, 2002), we estimate the number of factors, k, using the information criterion (IC) and the Bayesian information criterion (BIC). Specifically

$$IC(k) = \ln(V(k, \hat{f}^k)) + k\left(\frac{m+n}{mn}\right)\ln\left(\frac{mn}{m+n}\right) \tag{9}$$

$$BIC(k) = V(k, \hat{f}^k) + k\hat{\sigma}^2\left(\frac{m+n-k}{mn}\right)\ln(mn) \tag{10}$$

$$\text{where} \quad V(k, \hat{f}^k) = \frac{1}{m}\sum_{i=1}^{m}\hat{\sigma}_i^2, \qquad \hat{\sigma}_i^2 = \frac{1}{n}\hat{\varepsilon}_i'\hat{\varepsilon}_i, \qquad \hat{\sigma}^2 = \frac{1}{mn}\sum_{i=1}^{m}\sum_{t=1}^{n}E(\hat{\varepsilon}_i)^2$$

Given that our sample consists of 813 SME's each with 44 variables, we set $n = 813$ and $m = 44$. Table 2 shows the IC and BIC for the different values of $k \in \{1, 2, \ldots, 44\}$. For convenience, only the results of a selected few is shown in the Table. Figure 2 presents the plot of the IC and the BIC, which clearly indicates that the both criteria favors higher dimensions of k. Thus, $k = 44$ is selected based on the IC and BIC.

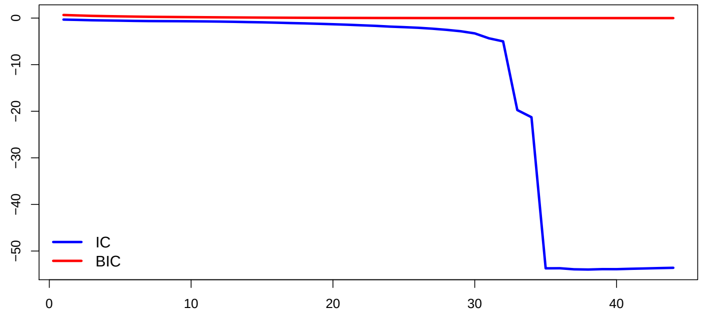


Figure 2: Plot of information criterion (IC) and the Bayesian information criterion (BIC) for the selection of the number of factors, k.

		Active		Defaulted	
	Variables	Mean	SDev	Mean	SDev
1	Fixed assets	349.06	593.54	381.68	1453.28
2	Intangible fixed assets	38.62	95.7	32.72	125.31
3	Tangible fixed assets	283.53	530.26	291.86	1130.79
4	Other fixed assets	26.91	161.16	57.1	399.81
5	Current assets	663.44	437.48	466.62	1077.46
6	Stock	161.54	268.85	80.22	258.76
7	Debtors	256.97	249.02	131.94	337.05
8	Other current assets	244.93	259.3	254.47	818.28
9	Cash	87.62	140.98	118.15	601.56
10	Total assets	1012.5	818.47	848.31	2296.79
11	Shareholder funds	275.85	512.5	-504.46	2631.02
12	Capital	44.85	94.33	138.96	689.08
13	Other shareholder funds	231	495.42	-643.43	3300.18
14	Non current liabilities	232.2	360.65	471.97	1993.71
15	Long term debt	69.67	203.91	187.05	1129.91
16	Other non current liab	162.53	260.8	284.92	1048.35
17	Provisions	13.18	56.29	92.51	426.27
18	Current liabilities	504.45	355.38	880.81	2821.72
19	Loans	94.18	154.91	191.19	1053.4
20	Creditors	181.1	197.19	248.18	1089.63
21	Other current liab	229.17	291.15	441.44	1342.65
22	Total shareholder funds & liab	1012.5	818.47	848.31	2296.79
23	Turnover	946.36	305.56	407.57	892.36
24	Sales	923.46	310.38	419.86	887
25	Profit loss	33.91	118.43	-181.85	496.42
26	Financial revenues	2.03	20.44	8.42	69.93
27	Financial expenses	13.24	21.36	23.93	103.57
28	Financial profit loss	-11.21	29.58	-15.51	64.34
29	Profit loss before tax	22.7	122.08	-197.36	530.35
30	Taxation	13.63	25.62	1.21	19.84
31	Profit loss after tax	9.07	105.39	-198.57	527.76
32	Other revenues	3.48	16.53	26.91	148.37
33	Other expenses	3.12	10.97	17.81	97.01
34	Leverage ratio	6.61	7.73	0.39	7.57
35	Total asset total liab	1.58	1.46	1.45	3.16
36	Current ratio	1.67	1.37	1.75	3.64
37	Quick ratio	1.35	1.26	1.59	3.62
38	ROI	1.83	4.5	-2.62	4.59
39	ROE	13.73	23.46	16.4	33.17
40	Asset turnover	1.32	0.83	1.17	3.89
41	ROS	0.04	0.06	-0.01	0.05
42	Debt conversion ratio	462.03	8630.04	-2712.46	27698.69
43	Debt ratio	0.78	0.33	5.67	37.38
44	ROCE	0.67	2.96	-1.92	4.82

Table 1: List and Summary Statistics of the variables in our sample.

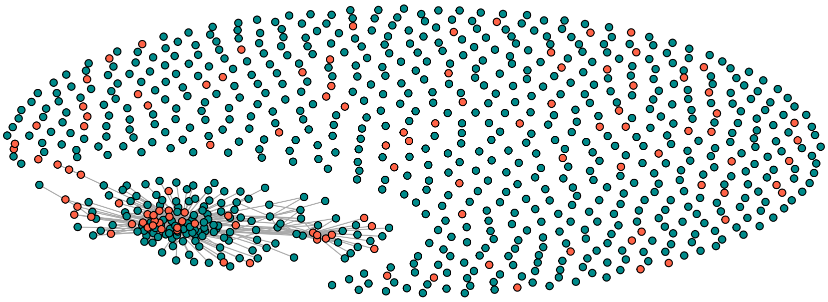
	IC	BIC
k=1	-0.3199	0.6641
k=2	-0.3860	0.5685
k=3	-0.4636	0.4811
k=4	-0.5104	0.4198
k=5	-0.5532	0.3678
k=10	-0.6888	0.2054
k=15	-0.9095	0.1054
k=20	-1.3197	0.0447
k=25	-1.9428	0.0153
k=30	-3.2834	0.0026
k=35	-53.7105	0.0000
k=40	-53.8910	0.0000
k=44	**-53.5963**	**0.0000**

Table 2: Comparing the information criterion (IC) and the Bayesian information criterion (BIC) for the selection of the number of factors, k. Boldface values indicate the best choice for each metric.

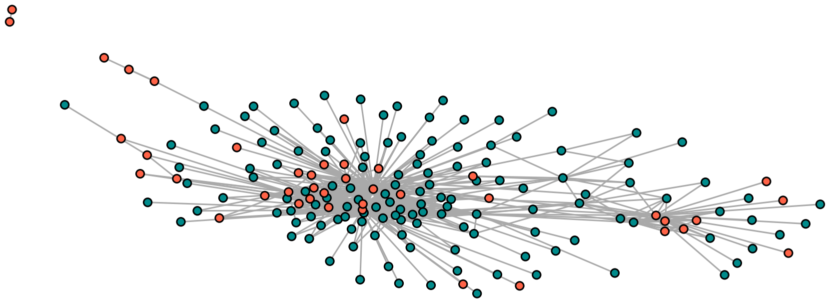
Using the SVD approach, we depict the network structure and the interconnections that emerge between companies participating in the P2P lending platform. In Figure 3, nodes are colored based on their status, with red indicating defaulted companies, and green active companies. The Figure contains two graphs: in Figure 3b nodes are equal sized whereas in Figure 3c nodes are proportional to companies' degree centrality. The choice of π_0 is set at 0.1 in correspondence with the proportions of defaulted companies in the overall sample. Although 0.1 is at a variance from 0.138 which is the precise proportion of defaulted companies in the sample, we use a round threshold as we found no significant difference between the number of links resulting from applying the two thresholds. Furthermore, we acknowledge that the proportion of defaulted companies within the sample is relatively high hence a more lenient approach to the process of link-inference could result in a more precise inference of the true network between the companies.

From the above graph the high interconnection that exists between active and defaulted SMEs is evident. The emergence of such linkages between companies provides evidence of the existence of joint unobservable forces linking P2P participants. From a credit risk viewpoint, if an active company is linked with a defaulted one, its credit scoring should decrease (contagion effect). Overall, network contagion seems to positively affect default, as the proportion of defaulted companies in Figure 3 is much larger than the observed proportion of defaults in the sample. Specifically, using the latent factor approach, in the community of connected nodes, 25% are companies which have defaulted which is significantly higher than the proportion of defaulted companies in the full sample which is 13.8%.

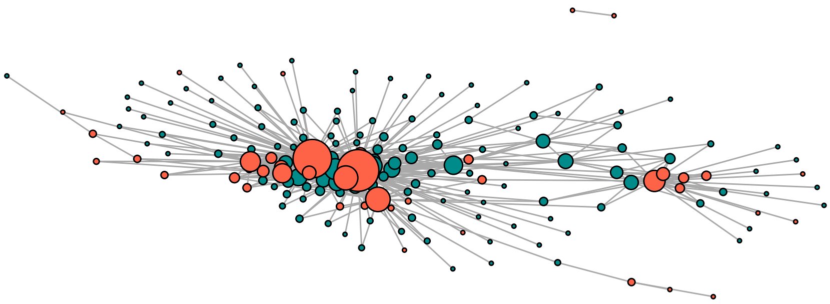
We remark that the identification of a network structure within the P2P lending systems could lead to the estimating on a more efficient scoring model. Namely, unlike traditional financial institutions which over the years have segmented their reference markets and in turn increased the accuracy of their scoring models, P2P platforms are based on a global and universal banking model hence developing a scoring model based on full inclusiveness of the data might lead to misleading results as it will capture the behavior and patterns of greatly varying units. In line with this, identifying underlining network structures and dividing the population into connected and not-connected nodes (based on the inferred latent variables), there is the potential of building a more efficient scoring model.



(a) Network Structure of All Institutions



(b) Network of Connected Component (Equal node sized)



(c) Network of Connected Component (Degree sized nodes)

Figure 3: Latent factor graph of participants in a P2P lending platform. (3a) shows both connected and non-connected participants in a P2P system, (3b) shows the connected component with equal sized nodes, and (3c) shows connected component where the size of nodes is proportional to their degrees. Nodes in green are active whiles defaulted participants are represented in red.

3.3. Predictive modeling

We now present the application of the latent factor approach for the purpose of improving the predictive performance of the credit scoring employed by P2P lending platforms. The available data include information on the status of the companies, classified as [1 = Defaulted] and [0 = Active] as well as information on the most important financial characteristics of the borrowers. This information can be used to specify and estimate a logistic regression model, aimed at predicting the default status, based on the observed values of the balance sheet variables. From the many available variables, we select a small number of them, based on the research literature as well as by means of a preliminary statistical significance analysis. Specifically, we rely on step-wise regression informed via the Akaike information criterion (AIC), to decide on the variables included in the final model. The variables included in the analysis are presented in Table 3.

Variables	How they are constructed / Description
Leverage ratio	Total current liabilities over shareholders funds
Debt to assets ratio	Total liabilities over total assets
Current ratio	Current liabilities over current assets
Quick ratio	Cash and cash equivalents over total assets
Return on investment	Profit/loss for period over total assets
Return on equity	Net income over shareholders' equity
Asset turnover	Operating revenue/total assets
Return on assets	Net income over total assets
Return on sales	EBIT/operating revenues
Return on capital employed	EBIT/sum of shareholders' equity & debt liab.
Debt coverage	Net income over total loans
Debt ratio	Total current liabilities over total assets

Table 3: Explanatory variables included in the scoring models and how they are constructed.

Using the variables in Table 3, we can specify and estimate the benchmark model employed in the credit scoring literature: the logistic regression model. Specifically, we estimate and compare three logit models: (i) full-sample scoring, (ii) scoring for connected nodes and (iii) scoring for not-connected nodes. We argue that because of P2P platforms' universal and global banking model, higher predictive utility can be achieved by applying a latent factor-based classification technique which divides the population into major communities (connected vs. not-connected companies).

Table 4 presents the results from the full-sample model which does not control for the network structures that emerge on the bases of the latent variables. We remark that the model in Table 4 has been derived after a thorough activity of model selection, aimed at obtaining the best fit statistical model.

Variable	Estimate	P-value	Significance
Intercept	-2.61	0.000	***
Leverage ratio	-0.09	0.000	***
Current ratio	-1.96	0.005	**
Quick ratio	2.19	0.002	**
ROI	-0.10	0.050	
ROE	0.02	0.000	***
ROS	-6.68	0.146	
Debt conversion ratio	-0.04	0.054	
Debt ratio	0.85	0.002	**
ROCE	-0.23	0.004	**
AUROC			0.856

Table 4: Full-sample scoring – Sample size: 813 companies

From Table 4 we note that all variables are statistically significant (at 10%) expect the return on sales variable. Although identifying causality is not the prime focus of the paper, we note that most of the coefficients have the expected sign except for the two ratios capturing liquidity and profitability performance of companies. Namely, the quick ratio and the ROE indicator report a positive and a negative sign, respectively which is contrary to our expectations. In the context of the quick ratio, the reported positive sign appears counter intuitive as it indicates that higher liquidity (measured via the quick ratio) increases the probability of default. Potential explanation for the positive sign can be in the fact that worst-performing companies tend to have higher liquidity due to their inability to invest in profitable prospects. Moreover, in the context of ROE, the results suggest that increasing ability of companies to use equity for generating profits increase the probability of default. This may be due to the fact that the companies investigated within this analysis are small businesses which do not rely extensively on equity financing.

As the main purpose of the analysis is to investigate the predictive utility of scoring models, we fit the models on a training set to make predications on a data that was not trained, and we consider the classification errors resulting from the models, the corresponding ROC curve and, finally, the Area Under the ROC curve (AUROC), the most widely-used measure of predictive performance for credit scoring models. The AUROC, which theoretically ranges between 0 and 1, is equal to 0.856, for the considered full sample model. Although the value of AUROC equal to 0.856 can be considered sufficient, a need to increase the accuracy of the model is always encouraged. Even small increases in accuracy can lead to significant savings due to a superior predictive performance, as argued by West (2000).

As previously commented, to improve the credit scoring accuracy, we introduce a network-based scoring. Specifically, we use the logistic estimator for connected and not-connected communities separately. Table 5 summarizes the results obtained from the scoring model for connected nodes.

Variable	Estimate	P-value	Significance
Intercept	-2.26	0.002	**
Leverage ratio	-0.05	0.187	
Current ratio	-3.29	0.024	*
Quick ratio	3.50	0.015	*
ROE	0.02	0.020	*
Debt ratio	0.86	0.059	
ROCE	-0.44	0.107	
AUROC			0.949

Table 5: Scoring for connected nodes – Sample size: 176 companies

Looking at the results for the connected nodes, similarly as it is the case with the full sample scoring, most of the variables are statistically significant and report the expected sign. ROCE remains insignificant potentially confirming the low-equity dependency of small businesses. Both the quick ratio and ROE keep the counterintuitive signs. We also note that in the context of connected companies, the liquidity ratios are among the main drivers which could be an indication of their exposure to contagion and systemic risk that in turn motivates them to keep higher liquidity.

In terms of predictive utility, the model, estimated only for the connected nodes, leads to an AUROC of 0.949 which is a significant improvement in scoring accuracy with respect to the model previously fit on all nodes. We remark that the difference between the two models are only in the node selection. Specifically, in the latter case, the model is estimated using the same methodology but only considering those companies which are connected (have at least one link with another company in the sample). Hence variable selection is consistent throughout the individual models. As mentioned previously, we employ stepwise regression including all the key financial ratios available in the dataset and consequently select the models that best fit the data according to the AIC criteria.

Variable	Estimate	P-value	Significance
Intercept	-0.94	0.110	
Leverage ratio	-0.06	0.052	
Quick ratio	0.28	0.298	
ROE	0.02	0.018	*
Asset turnover	-2.70	0.000	***
ROS	-18.34	0.001	**
Debt conversion ratio	-0.01	0.537	
Debt ratio	1.44	0.001	**
ROCE	-0.22	0.012	*
AUROC			0.945

Table 6: Scoring for not-connected nodes – Sample size: 637 companies

Finally, we investigate the scoring model for not-connected companies. Table 6 summarizes the results. Looking at the results for the non-connected nodes, we see that most variables are found statistically significant except for the quick ratio and the debt conversion ratio. The AUROC reported is 0.945 which is like the predictive utility of the scoring model for the connected nodes. In the attempt to validate the results, robustness checking has been carrying out by changing the π_0 threshold. We have confirmed that the community detection approach results in higher predictive utility relative to the full-sample scoring if the π_0 threshold is changed to 0.138, 0.2 and 0.3. Furthermore, another robustness check performed is that of random sub-sampling. Specifically, to confirm the validity of the results, we ran the same analysis considering many different random subsets. Specifically, we divided the sample of 813 companies on two random subsets (keeping the same proportion between connected and not-connected companies) and re-ran the analysis with several different seeds.

The average AUC for the random subsets with sample sizes equal to the connected and not connected communities are: 0.8618256 and 0.8555784, respectively. These predictive utilities are significantly lower compared to those obtained by splitting the sample based on the SVD approach. We believe that these results are a clear indicator that a latent factor-based classification technique that divides the population into major communities based on the SVD approach does lead to the estimation of a more efficient logistic model, which in turn is crucial to improving credit risk measurement. The approach of identifying communities of connected and not-connected nodes, in a way, mimics the segmentation strategies employed by traditional financial institutions which in turn allows P2P platforms to obtain high predictive accuracy of the scoring model without necessarily possessing all the financial and non-financial information about individual participants in the platform. Furthermore, the proposed methodology can also help traditional financial providers to improve their scoring by further "segmenting the segments".

Finally, our results can be put in context of a similar research carried out by Giudici and Hadji-Misheva (2017) which aim is to investigate whether the inclusion of network parameters (obtained from correlation networks) into a traditional credit scoring approach can improve the model's overall predictive utility. The study confirms this premise as the inclusion of the network-derived parameters improves the predictive accuracy of the scoring by several percentage points. However, the approach presented in this paper enables a more precise differentiation of risk classes as the network is inferred based on all known financial parameters which in turn lead to a much higher predictive utility.

4. Conclusions

This paper contributes to the recent development on P2P lending credit risk modeling in that it shows how scoring models can be improved, using the information that is automatically collected by P2P lenders, which typically connect borrowers, in a well-connected network of relationships and transactions. Such network structure extends beyond the classical geographical and economic sectors. Information that can be embedded into financial network models, can capture non-linearities and endogenous factors that explain the spread of credit risk through the network.

The application of our proposed network-based scoring model demonstrates that the model is appealing, not only theoretically but also, from an operational point of view, as it increases predictive accuracy of the default, thereby better protecting lenders and improving financial stability. We believe that the main beneficiaries of our results may be regulators and supervisors, aimed at preserving financial stability, as well as investors of P2P platforms, whom should be protected against the negative sides of FinTech innovations (related with information asymmetries) while keeping their positive sides (related with the improvement of of data availability and processing).

Acknowledgments

Authors' research is supported by funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 825215 (Topic: ICT-35-2018 Type of action: CSA); and the US Air Force Office for Scientific Research (AFOSR), whose grant number is FA9550-12-1-0102.

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