ECONOMICS & Sociology

Gavurova, B., Dujcak, M., Kovac, V., Kotásková, A. (2018). Determinants of Successful Loan Application on Peer-to-Peer Lending Market. *Economics and Sociology*, *11*(1), 85-99. DOI: 10.14254/2071-789X.2018/11-1/6

DETERMINANTS OF SUCCESSFUL LOAN APPLICATION AT PEER-TO-PEER LENDING MARKET

Beata Gavurova,
Technical University of Košice,
Košice, Slovak Republic,
E-mail: beata.gavurova@tuke.sk

Martin Dujcak,
Technical University of Košice,
Košice, Slovak Republic,
E-mail: martin.dujcak@tuke.sk

Viliam Kovac,
Technical University of Košice,
Košice, Slovak Republic,
E-mail: viliam.kovac@tuke.sk

Anna Kotásková,
Pan-European University in Bratislava,
Bratislava, Slovak Republic,
E-mail: anna.kotaskova@gmail.com

ABSTRACT. Peer-to-peer lending, as an alternative to classic bank loans, has become popular all over the world. On the basis of the conceptual characteristics, it can be expected that loans should be more advantageous from the view of costs. But as the studies describe, there are significant differences due to the factors, which can be affected by borrowers with the aim to get funded. We have examined the role of the particular factors, as part of provided data by borrowers for the decision-making process by investors in the dataset from the peer-to-peer lending website Bondora, managed by the Estonian company Isepankur. With the method of the multinomial logistic regression model, we described the importance of borrowers' decisions and their effects on funding results. The debt to income rate is the most significant variable and the highest negative impact is reached by the home ownership type variable. There are 28 factors with a non-negative impact and 20 factors have a negative influence. Comparison of these findings to other studies enable us to describe the impacts of the social identity data and information about the loan for investors, within the peer-to-peer lending market environment.

Received: October, 2017
1st Revision: December, 2017
Accepted: February, 2018

DOI: 10.14254/2071-789X.2018/11-1/6

JEL Classification: H81, L81

Keywords: peer-to-peer lending; loan application; financial marketplace; electronic commerce.

Introduction

Despite the existence and still remaining popularity of classic banking loans there has always been a place for the concept of interpersonal loans. In the course of information technologies' evolution, especially during the last decade, this concept has been transformed to an electronic form. This shift of interpersonal loans to electronic markets where traditional intermediaries may be less important or even redundant for the economic interaction of market participants leads to rapid growth of popularity, as reflected in the raising number of lenders and borrowers.

Peer-to-peer lending has been developed from the concept of crowdsourcing (Howe, 2006). The basic idea of crowdfunding is to raise external finance from a large audience, named also a crowd, while each person – investor – provides a very small amount, this is done instead of soliciting a small group of sophisticated investors (Belleflamme *et al.*, 2011). Peer-to-peer lending is distinguished as one of the crowdfunding types and is characterised as loan accumulated by a few people in the position of investors, who lend their money to borrower for a particular period and get reward in the form of interests (Hemer *et al.*, 2011; Kortleben and Vollmar, 2012; Michalski, 2014; Bem and Michalski, 2015; Falola *et al.*, 2017).

Since 2006, when the first of the platforms for online mediation of interpersonal lending was established in the United Kingdom, their development has been steadily progressing. Today, a huge increase is seen in the popularity of the portals like Prosper or Lending Club in the United States, Peer-to-peer Downloading Amount and My089 in China, Popfunding in South Korea and Smava in Germany. Moreover, these markets have become international, as for instance Bondora by Isepankur, which was established in Estonia and offers the possibility to borrow money in four countries nowadays and through this way to receive funds from investors located in one of 37 countries. In spite of the fast rising popularity of peer-to-peer lending and the growing role of e-commerce, this issue has received only a limited attention in research literature (Chen *et al.*, 2014; Rutkowska-Podolska and Michalski, 2015; Szczygieł *et al.*, 2015; Dusatkova and Zinecker, 2016).

The recent research studies in this regard have been focused on the three key aspects:

– development and expansion of the peer-to-peer lending concept;
– factors influencing the share of successful applications and the default risk level;
– profitability of loans at a certain level of risk (Emekter *et al.*, 2015).

This study concerns the second of the aspects mentioned above. It focuses on the decision-making process of investors choosing from a variety of investment opportunities at the peer-to-peer lending online market according to their specific features. The output of the study is valuable also for the borrowers at the same market as it provides information which may determine whether the loan application will be funded or not.

1. Literature review

When decision makers in position of investors consider a particular offer, they rarely have perfect information about potential transaction partners (Grčić Fabić *et al.*, 2016; Jovanović *et al.*, 2016). They have to decide whether to engage in the exchange and about the terms using the best information available (Sonenshein *et al.*, 2011; Cipovová and Belás, 2012; Hagyari *et al.*, 2016; Bożek and Emerling, 2016; Jonek-Kowalska, 2017). One of the problems in online peer-to-peer lending is information asymmetry between the borrower and the lender what might result in adverse selection (Akerlof, 1970). In the context of peer-to-peer lending it means that lender does not know the borrower's credibility as well as the borrower does (Emekter *et al.*, 2015). As it is a still new way of investing and borrowing money, the anonymity of the online peer-to-peer lending market may cause borrowers to exhibit greater uncertainty based on information asymmetry (Luo and Lin, 2013). This could be reduced by regular monitoring of transactions what is possible regarding electronic records (Gąsiorowski, 2016). On the other hand, the nature of peer-to-peer lending means that such a recording of data describing interactions may not be possible, as the majority of all the loans are one-shot events. That is, borrowers usually apply for and receive a loan just once (Feller *et al.*, 2014) and analysis is rather difficult, moreover some authors say it is not available (Herzenstein *et al.*, 2011). Basically, investors in peer-to-peer lending compose their decision on the basis of two data types – hard and soft data. Hard data is defined as providing accurate information as it is able to strictly quantify it, simply to record and to store it and effectively transform (Petersen, 2004). In the context of peer-to-peer lending information like credit score can be included to this group, reflecting accumulated financial interactions across a range of domains (Feller *et al.*, 2014). The information is provided as evaluation of the peer-to-peer lending platform or the external agency with an aim to provide more trusted information. Other historic data concerning the applicants' previous financial behaviour involves for instance the past delinquencies and their performance or more positive information about the past fully repaid loans. Classic information, which borrowers provide, are also income in the form of accurate sum or interval, sometimes selected into a few groups, data about monthly costs, homeownership status and information about their past and actual jobs.

While hard information is usually obligatory, it is voluntary to provide also soft information. But as the studies prove, soft information can support to create trust and complement hard information. Through them borrowers can diminish information asymmetry the market participants.

In addition to the required information for borrowers on individuals, there is an opportunity to make other information transparent in the context of its loan description. In the trust terms, providing additional information may reduce information asymmetry between borrowers and lenders, (Feller *et al.*, 2014) and so can be interpreted as a gesture of benevolence intended to convey a borrower's strong intentions of repayment (Pötzsch and Böhme, 2010).

There have been identified three basic dimensions of optional soft data:

– additional credit information;
– personal or humanising information;
– direct appeals made to lenders.

1.1. Effect of provided information on funding probability

Applied amount is the first aspect among the basic factors with very strong effect on successfulness of application for a loan. In general, investors prefer request for lower sums than the ones with higher sums, which are connected with higher level of risk naturally (Herzenstein *et al.*, 2008; Ravina, 2008; Barasinska, 2011; Herzenstein *et al.*, 2011; Pope and Sydnor, 2011; Sonenshein *et al.*, 2011; Constantinescu and Drăgoi, 2015; Michalski, 2016).

The second important factor is acceptable interest rate offer for borrower (Freedman and Jin, 2008; Herzenstein *et al.*, 2008; Barasinska, 2011; Sonenshein *et al.*, 2011; Sanusi *et al.*, 2017). As it was written by Qiu *et al.* (2014), borrowers's decisions – loan amount and interest rate – will determine whether loan will be successfully provided or not. As the studies show, investors like more applications where interest rate is higher due to the natural character of investment process and also because higher interest rate can sign that borrower believes, according to the data, that offer will attract enough investors which via their bids cause decrease of offered interest rate.

The third basic factor with strong influence is duration of the loan with the positive effect – raising duration means raising the probability of funding loan (Hildebrand *et al.*, 2010; Barasinska, 2011; Feller *et al.*, 2014; Žurga, 2017). This effect is partly caused by lowering the risk as the long duration has the effect of lower monthly payments which brings lower risk of later payments in comparison of the same loans in the shorter period. Some authors claim that the purpose of the loan, explicitly the aim to use the loan as entrepreneur, can have negative effect on the probability of funding (Herzenstein *et al.*, 2008; Pope and Sydnor, 2011; Sonenshein *et al.*, 2011). On the other hand, the other authors identify positive effect of the information (Ravina, 2008; Barasinska, 2011; Bánociová and Martinková, 2017).

Moreover, there is also opinion that investors do not react very strongly to the stated purpose of the loan (Pope and Sydnor, 2011).

One of the main significant aspect is also impact of the debt-to-income ratio in the meaning that it raises funding probability negatively (Herzenstein *et al.*, 2008, 2011; Hildebrand *et al.*, 2010; Weiss *et al.*, 2010; Pope and Sydnor, 2011; Sonenshein *et al.*, 2011).

Controversial effect is discussed for the factor homeownership status. Some studies claim its positive effect (Ravina, 2008; Hildebrand *et al.*, 2010; Weiss *et al.*, 2010; Herzenstein *et al.*, 2011) as it is indicative of stability and a prior ability to access credit to obtain a mortgage (Herzenstein *et al.*, 2011). But general opinion of investors varies as an estimated value can widely differ from the market value in the case the value of flat or house is not proved by external agency.

Rating evaluation is recognised as very significant factor and as it is natural, the better rating, the better chance to be funded (Herzenstein *et al.*, 2008, 2011; Ravina, 2008; Weiss *et al.*, 2010; Barasinska, 2011; Pope and Sydnor, 2011; Sonenshein *et al.*, 2011).

Data about past or currently not fully repaid credits are not very significant in general. Some papers show slightly negative effect of bankruptcies or presence of other credit lines (Ravina, 2008; Weiss *et al.*, 2010; Sonenshein *et al.*, 2011).

Information describing education is identified as not significant (Ravina, 2008; Herzenstein *et al.*, 2011; Gavurova *et al.*, 2017), but some types of information about employment can help application for a loan, like for instance longer duration of employment. Different knowledge about the impact of employment status was presented, while the retired and unemployment statuses cause according to the findings positive effect on probability of funding (Ravina, 2008; Herzenstein *et al.*, 2011). On the other hand, Barasinska (2011) claims its negative effect what can be caused by the different data applied – the Prosper data versus the Smava data.

About the gender and age, Pope and Sydnor (2011) show that these aspects, together with other personal characteristics like weight, race, appearance and other personal characteristics, seriously impact successful rate and so there is proved discrimination on the platforms of peer-to-peer lending markets.

So, during last years, a number of research analyses have been made identifying the effect of provided information on funding probability. But, most of them focus just on the behaviour within one online platform. To be able to accept the rules generally, there is a need to identify new available data and compare the findings with the others authors, describing the borrowers and investors in other countries using the different platforms, as their specific attributes can significantly influence the final outputs.

2. Data and methodology

In the previous sections, the findings from the studies focusing on personal transparency and lending behaviour on the peer-to-peer lending platforms are described. The relations are defined on the base of the data from a range of the platforms, including mainly Prosper available on https://www.prosper.com and Smava on https://www.smava.de, which are most popular for the research purpose. As the next step, we propose to use the data from the other platforms for the same purpose what would bring new findings and enable us to define whether these relationships are consistent across the whole peer-to-peer lending environment. It means, if the effect of the particular type of the data is the same without dependence of the specific tools presence provided by the particular platform.

2.1. Data

For the purpose of our research, we identified as suitable the data from the Estonian company Isepankur. It is provider of the platform Bondora which is one of the leading platform for investing in European personal loans. Since 2009, they have processed over 400 million euro of loan applications from prime and near-prime borrowers. Till today, more than 9 000 investors from 37 countries have funded 35 million euro in loans and received over 4 million euro as interest payments. Bondora was one of the first platforms which enable cross-border lending. Nowadays, people from all the European countries can invest through it and people from four countries can apply for a loan. The dataset describes applications for a loan for the time period since 2009, when Bondora came to the market, to the end of 2015. Each case is described through 201 characteristics. We chose just of some of them which are relevant for application for a loan and known at the moment when borrower submit demand for money. Format of some factors was changed in an appropriate way. Finally, there were 46 916 records in the dataset. This makes the potential outcomes from the analysis relevant.

Table 1. Structure of Loan Applications

State	Number
inactive duplicate	2 576
refused loan applications	19 227
active loan listings	7 955
successful loan applications – paid	12 439
successful loan applications – currently not paid	4 719
overall	46 916

Source: own elaboration by the authors.

In the next step, we applied the process of the data preparation – clearing of the invalid records, transformation and reduction we got the final data base, including 43 515 records. For our purpose – to analyse factor impacting decision of investors – we assumed our database as suitable. There are 25 874 successful loan applications and 17 461 unsuccessful loan applications in the dataset.

2.2. Methodology

There are several tests performed to verify the desired outcomes – the analysis of variance (Fischer, 1921), the sensitivity analysis in form of the regression analysis (Birkes and Dodge, 1993) and the test of residuals normality (Jarque and Bera, 1980).

Firstly, the analysis of variance was performed – in order to identify, if there is the impact of the variables on the investors' decision, the analysis of variance was chosen in order to analyse the differences among the group means.

There are these hypotheses verified:

– $H_0: F_1(x) = F_2(x) = \ldots = F_i(x) = \ldots = F_n(x);$

– $H_1: \exists\, i: F_i(x) \neq F_j(x).$

The null hypothesis H_0 was tested on the chosen level of significance α. It represents a state when for every real x, which all the selections are from the same distribution for. Against, the alternative hypothesis H_1 stands – it means at least one selection is different from the others. If the p-value is lower than the selected significance level, the null hypothesis is rejected. In this case a five-per-cent significance level is applied. This means that the difference between at least one pair of median values calculated from the sample is too large, it can only be the result of random selection – therefore, it is statistically significant. Hence, there is a relationship between the variables. If the p-value is equal to the significance level or greater than the significance level, the null hypothesis cannot be rejected. This implicates that the difference between each pair calculated from the median values of the sample can only be the result of a random selection. Therefore, it is not statistically significant – there is no relationship between the variables.

Secondly, the sensitivity analysis was performed. The logistic regression was the selected form of this analysis to be accomplished. This decision was made according to the character of the source dataset and the observed dimensions. The dependent variable is represented by the information whether an application for a loan was funded or not. This represents the binary stats of the explored variable. That is why, the decision to examine the logistic regression was done.

In general, the logistic regression approach is preferred against the casual type as the casual type is not suitable for the purpose of the analysis. Also, there are the authors who proved its suitability through an application to the data from the other peer-to-peer lending markets (Zheng *et al.*, 2014; Puro *et al.*, 2010).

The logistic regression is based on the cumulative logistic probability function described as (Pindyck and Rubinfeld, 1997; Kovacova and Kliestik, 2017):

$$f(z) = \frac{1}{1 + e^{-z}}$$

where the variables mean:

– z – dependent variable;
– e – Euler's number.

The formula describing probability of funding, as z is dependent on the set of the variables (Pindyck and Rubinfeld, 1997):

$$z = \beta_0 + \beta_1 . x_1 + \dots + \beta_i . x_i + \dots + \beta_n . x_n$$

where the variables represent:

– z – dependent variable;
– β_0 – constant value;
– β_i – estimated regression coefficient of the ith variable;
– x_i – the ith variable;
– n – number of variables.

There are 27 variables involved in the analysis, that is why n is equal to 27 in this case. The two types of the dimensions are involved in the study – discrete variable and continuous numerical variable. The discrete dimensions are represented by the factor variables. There are 20 continuous numerical variables and 7 discrete variables. They are listed in *Table 2*.

Table 2. Factors and Additional Credit Information

Variable	Factor	Alternative	Description
1	*2*	*3*	*4*
PAA	previous applications amount		amount of previous applications for a loan
PLA	previous loans amount		amount of previous realised loans
AT	application type	1	timed funding
		2	quick funding
AA	applied amount		amount which borrower applied originally for
BCC	bank credits count		count of credits provided by banks
DTIR	debt to income rate		ratio of borrower’s monthly gross income that goes toward paying loans
E	education	0	primary education
		1	basic education
		2	vocational education
		3	secondary education
		4	higher education
ED	employment duration		duration of current employment
FC	free cash		discretionary income after monthly liabilities
G	gender	0	male
		1	female
		2	undefined gender
HOT	home ownership type	0	homeless
		1	owner
		2	living with parents
		3	tenant, furnished property
		4	tenant, unfurnished property
		5	council house
		6	joint tenant
		7	joint ownership
		8	mortgage
		9	owner with encumbrance
OI	other income		borrower’s income from other sources
PLI	paternal leave income		income in form of paternal leave
IR	interest rate		maximum interest rate accepted in the loan application
LD	loan duration		current loan duration in months
NO	new offer	0	new offer made
		1	new offer not made
PL	previous loans		number of previous loans
D	dependants		number of children and dependants
OL	other liabilities		other liabilities before loan
PLF	previous late fees		previous late fees paid
PR	previous repayments		previous repayments made
BR	Bondora rating		Bondora rating issued by the rating model
BC	bank credits		sum of bank credits
OC	other credits		sum of other credits
VT	verification type	0	income unverified
		1	income unverified, cross-referenced by phone
		2	income verified
		3	income and expenses verified
LBL	liabilities before loan		total liabilities before loan application

1	*2*	*3*	*4*
ML	monthly liabilities		total monthly liabilities
F	funding	0	funded
		1	not funded

Source: own elaboration by the authors.

Thirdly, testing of the residuals was performed. It is needed that the values of the residuals have to come from the normal distribution of probability. To determine the appropriate methods of testing the impact of the input variables, it is obligatory to assess whether the data sample meets the conditions of the residuals normality.

3. Analysis

The test of normality, by the Kolmogorov-Smirnov test, showed us that almost all the variables in the dataset were not normally distributed. As the next step, correlation analysis was made on the base of the method of the Kruskal-Wallis test, which is an extensive form of the Mann-Whitney nonparametric test and it represents an alternative to the one-way analysis of variance.

Table 3. The Kruskal-Wallis Test for the Individual Factors

Factor	Test statistic	P-value
PAA	7.743	0.005
PLA	1307.966	0
AT	136.901	0
AA	1663.193	0
BCC	48.104	0
DTIR	10429.948	0
E	325.869	0
ED	58.269	0
FC	4836.15	0
G	200.408	0
HOT	4.862	0.027
OI	177.059	0
PLI	81.194	0
IR	3486.394	0
LD	1348.266	0
NO	545.142	0
PL	1331.592	0
D	38.281	0
OL	1024.826	0
PLF	294.678	0
PR	743.719	0
BR	5167.758	0
BC	136.806	0
OC	1448.746	0
VT	2024.297	0
LBL	1959.217	0
ML	1.092	0.296

Source: own elaboration by the authors.

As seen, in *Table 3*, the p-values of the test statistics of the individual variables conducted by the Kruskal-Wallis test confirm the expected state. These values except for one reject the null hypothesis meaning the samples come from the same probability distribution. Therefore, it can be stated the difference between at least one pair of medians calculated from the sample is too large to be only the outcome of random selection. Hence, it is statistically significant meaning there is a relationship between the variables.

The test confirmed the prediction that the input variables have impact on the output variable – the decision of investors if they will fund the borrower or not. But according to this analysis, another important issue was found out too. Some pairs of variables have too high correlation rate. For that reason, we started to remove one of such pairs, until all the correlations rates were under 0.3. This border was set as sufficient, as this rate is the boundary between medium and low rate of correlation. After this process, there is a set of the following variables described in *Table 2*.

Following that, the first regression model was made. Its prediction rate is at level of 78.8%. The first model included the several insignificant variables. Hence, we started with their reduction. After the several steps, the final model was composed – with the prediction rate at level of 79.6% – including only the statistically significant variables with the p-values under level of 0.1.

Table 4. Classification Table for the Final Regression Model

		Predicted variable		Prediction rate
		Funded – 0	Funded – 1	
Observed variable	Funded – 0	8503	4409	65.9 %
	Funded – 1	3127	20853	87 %

Source: own elaboration by the authors.

As it can be seen in *Table 4*, the prediction rate of the model was better for the cases, when application for the loan was successful, as there was a share of 87% of the right predictions and in the cases of not funded, only a share of 65.9% was correct.

Table 5 demonstrates the estimated regression coefficients of the variables involved in the final regression model, hence their impact on success of application for loan is visible.

Table 5. The Final Regression Model

Variable	Option	β	Standard error	Wald test	Degrees of freedom	Significance	Odds ratio
1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
PAA		0	0	67.35	1	0	1.00
PLA		0	0	11.01	1	0	1.00
AT		-1.62	0.16	105.47	1	0	0.20
AA		0	0	683.36	1	0	1.00
BCC		-0.23	0.03	69.68	1	0	0.79
DTIR		5.74	0.17	1154.64	1	0	310.57
E				73.54	4	0	
	1	-0.39	0.09	18.99	1	0	0.68
	2	-0.24	0.05	25.58	1	0	0.79
	3	-0.24	0.04	42.78	1	0	0.79
	4	-0.04	0.04	0.94	1	0.33	0.96
ED		-0.03	0.01	24.50	1	0	0.97

1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
FC		0	0	89.93	1	0	1.00
G				516.70	2	0	
	1	1.08	0.05	454.36	1	0	2.93
	2	1.17	0.05	491.99	1	0	3.21
HOT				132.71	9	0	
	1	-1.87	0.92	4.12	1	0.04	0.15
	2	-1.01	0.20	24.68	1	0	0.36
	3	-1.21	0.21	34.91	1	0	0.30
	4	-1.02	0.21	24.74	1	0	0.36
	5	-1.21	0.21	34.58	1	0	0.30
	6	-1.3	0.22	34.50	1	0	0.27
	7	-1.24	0.22	32.84	1	0	0.29
	8	-1.08	0.21	26.03	1	0	0.34
	9	-0.66	0.21	10.01	1	0	0.52
OI		0	0	37.51	1	0	1.00
PL		0	0	7.80	1	0.01	1.00
IR		0.34	0.11	9.57	1	0	1.41
LD		-0.02	0	621.64	1	0	0.98
NO		1.22	0.08	216.54	1	0	3.38
PL		0.06	0.03	4.51	1	0.03	1.06
D		0.03	0.01	3.22	1	0.07	1.03
OL		0.19	0.02	100.87	1	0	1.21
PLF		0	0	5.85	1	0.02	1.00
PR		0	0	12.97	1	0	1.00
BR				1741.32	7	0	
	1	1.84	0.16	137.84	1	0	6.29
	2	2.62	0.46	31.96	1	0	13.80
	3	2.42	0.10	583.46	1	0	11.20
	4	1.82	0.06	948.13	1	0	6.20
	5	1.63	0.05	1043.51	1	0	5.08
	6	1.20	0.04	762.25	1	0	3.32
	7	0.88	0.05	375.99	1	0	2.41
BC		0	0	134.53	1	0	1.00
OC		0	0	40.76	1	0	1.00
LBL		-0.09	0.01	76.63	1	0	0.92
ML		0	0	93.86	1	0	1.00
VT				140.79	3	0	
	1	-0.31	0.04	50.37	1	0	0.73
	2	2.07	0.40	26.73	1	0	7.90
	3	-0.43	0.04	105.90	1	0	0.65
constant		1.28	0.23	31.29	1	0	3.59

Source: own elaboration by the authors.

In *Table 5*, the elementary statistics data for the final version of the logit model. As it is seen, the categorical variables were split into the several dummy variables to be possible to assess their impact on the dependent dimension – success of application for a loan. The column β demonstrates the estimated regression coefficient describing the impact on the output variable. According to the values in the column with the coefficient of statistical significance, based on the Wald test, it is seen that all the variables have significant impact on the dependent dimension, as their values are lower than the significance level.

The most significant variable is the debt to income rate with the estimated beta coefficient at a level of 5.74. The highest negative impact is reached by the home ownership type owner – at a level of -1.87. Altogether, there are 28 factors with a non-negative impact in the model, whilst 20 factors have a negative influence. Only two factors are not statistically significant – the education status higher education and the number of children and dependents.

4. Results and discussion

The analysis brought the various conclusion for the factors, which has been previously tested by the other authors. Some effects were proven, some disproved and the other still remain not fully understood in the context. In the process of investment decision making, the lender tries to gain as much information as possible to assess in the best way the profit and its probability to be reached. One of the aspects the investor focus on is the history of the borrower in whatever a point of view.

The variables, which describe the borrower's behaviour, on the peer-to-peer lending platform seems to be irrelevant for the investors, as previously applied amounts either number of previous applications have no impact on its potential to be funded. But this can be caused also by the structure of the database, in which the majority of the transactions are just onetime actions, not regular activities what would generate enough data needed for deeper analysis.

On the other hand, significant effect of the historical behaviour outside the platform can be seen via the variable describing previous credits and loans. It has to be highlighted that the only significant factor is count of other credits, not their amount, just as was the conclusion of Hildebrand *et al.* (2010).

Another widely discussed factor reflecting the history of borrower is rating. As expected, the better is rating class, the higher is probability of successful listing, as was proved by most of the authors in the field.

The debt to income rate is another factor reflecting the background of the borrower. It is usually considered as very significant. Its estimated beta coefficient reaches value of 5.74 making it the most significant variable from this point of view. Such a fact was proved also by our study, as well as studies based on the Prosper data (Herzenstein *et al.*, 2008, 2011; Hildebrand *et al.*, 2010; Weiss *et al.*, 2010; Pope and Sydnor, 2011; Sonenshein *et al.*, 2011). Obviously, there is the question, which one of the composing variables – debt and income – has higher significance in this context. As it can be seen in the table of the analysis outcome, none of the income type was identified as significant in the model what is the opposite in comparison with the conclusions of the analysis of the Prosper data (Ravina, 2008; Hildebrand *et al.*, 2010; Herzenstein *et al.*, 2011).

On the other hand, liabilities seem to be effecting the status of funding. As it is demonstrated, also the personal characteristics of borrower are perceived as important information to the investors.

The gender discrimination was proven, as seen in *Table 5*, while women have higher successful rate when applying for a loan on the platform Bondora, what complies with the findings of Pope and Sydnor (2011). Estimated coefficient of 1.08 belongs to male gender, whilst estimated coefficient of 1.17 is assigned to female gender.

And as it was found out, person with higher education achieved, have better probability to be funded. History of borrowers is analysed also from the point of home ownership, what was identified as the factor with a significant impact, the same as on the Prosper data (Hildebrand *et al.*, 2010). All the variables possess negative impact on the dependent dimension – -0.39, -0.24, -0.24, and -0.04 – from basic education through vocational education and secondary education to higher education.

One of the main significant factors, identified by the other studies too, is the applied amount of the listing for the loan. According to the studies based on the Prosper data, the investors do not prefer listing with high applied amount (Herzenstein *et al.*, 2008, 2011; Ravina, 2008; Barasinska, 2011; Pope and Sydnor, 2011; Sonenshein *et al.*, 2011). But the finding coming from this analysis is that the factor does not effect – positively or negatively – the probability of successful listing.

Another interesting point also from a psychological angle of view, based on the theory of risk aversion, is that higher investment brings higher risk for the investor. But, as it is seen in the outcome table above, the prediction saying that the higher is interest rate, the higher is probability of being funded, was proven. It complies with the other studies (Barasinska, 2011; Freedman *et al.*, 2008; Herzenstein *et al.*, 2008; Ravina, 2008; Pope and Sydnor, 2011; Sonenshein *et al.*, 2011). The estimated coefficient of the interest rate variable is at level of 0.34.

As the important dimension the trust rate of provided information by borrower was identified too. It was identified via the factor of the verification type. The most interesting state of this variable is the status 0 which means income unverified. It has a higher positive effect on the probability of being funded than level 1 meaning the status income unverified and cross-referenced by phone with the estimated coefficient of -0.31. We should also think about the possible reasons, why the status 2 income verified has a significantly better impact for borrower at estimated level of 2.07 than the status 3 income and expenses verified with the regression coefficient of -0.43.

Conclusion

This study is focused on the particular type of crowdfunding concept which has become more and more popular during the last decade, what is the reason that there is coming out the natural need to pay more attention to this field of funding, also in the form of the behaviour analysis within the electronic platforms which mediate networking between the demand side of the market and the supply side of the money market. Through the performed analysis, we tried to give an opportunity to improve the concept and its processes clearer, mainly from the view of the factors effecting the probability of the successful loan listing. There were the several general rules found out that can be observed without the limits of the geographical borders or the cultural boundaries – like for instance, applied amount or interest rate are. On the other hand, some of the effects, which were expected, did not occur in the real transactions and they will be examined in our further research activities – to perform the deep analytical investigations on these factors particularly.

Acknowledgements

This work is created within the project supported by the Scientific Grant Agency of the Ministry of Education, Science, Research and Sport of the Slovak Republic and the Slovak Academy of Sciences 1/0978/16 Financial health of companies and their importance in the context of supplier-consumer relations.

References

Akerlof, G. (1970). The market for lemons: quality uncertainty and the market mechanism. *Quarterly Journal of Economics,* 84, 488-500.

Barasinska, N. (2011). Does Gender Affect Investors' Appetite for Risk? Evidence from Peer-to-Peer Lending. *German Institute for Economic Research Discussion Paper Series*, 1125, 1-32. DOI: 10.2139/ssrn.1858719.

Bánociová, A. and Martinková, S., (2017). Active Labour Market Policies of Selected European Countries and Their Competitiveness. *Journal of Competitiveness*, *9*(3), 5-21. DOI: 10.7441/joc.2017.03.01. Available online: http://www.cjournal.cz/files/254.pdf. Referred on 4. 7. 2017.

Belleflamme, P., Lambert, T. and Schwienbacher, A. (2011). Crowdfunding: Tapping the Right Crowd.

Bem, A. and Michalski, G. (2015). *Hospital Profitability vs. Selected Healthcare System Indicators*. Central European Conference in Finance and Economics 2015, Technical University of Košice, 52-61.

Birkes, D. and Dodge, Y. (1993). *Alternative Methods of Regression*. Hoboken: Wiley. 240 p.

Bożek, S. and Emerling, I. (2016). Protecting the organization against risk and the role of financial audit on the example of the internal audit. *Oeconomia Copernicana*, *7*(3), 485-499. DOI: https://doi.org/10.12775/OeC.2016.028.

Cipovová, E., Belás, J. (2012). Assessment of Credit Risk Approaches in Relation with competitiveness Increase of the Banking Sector. *Journal of Competitiveness*, *4*(2), 69-84. DOI: 10.7441/joc.2012.02.05. Available online: http://www.cjournal.cz/files/96.pdf. Referred on 23. 9. 2017.

Chen, N., Ghosh, A. and Lambert, N. S. (2014). Auctions for social lending: A theoretical analysis. *Games and Economic Behavior*, 86, 367-391. DOI: 10.1016/j.geb.2013.05.004.

Constantinescu, L. M., Drăgoi, V. E. (2015). An assessments of the banking system performence of Romania & United Kingdom during the last financial crisis. *Polish Journal of Management Studies*, *11*(1), 17-27.

Dusatkova, M., Zinecker, M. (2016). Valuing start-ups – selected approaches and their modification based on external factors. *Business: Theory and Practice*, *17*(4), 325-344. https://doi.org/10.3846/btp.17.11129

Gąsiorowski, J. (2016). Managing security in electronic banking – legal and organisational aspects, *Forum Scientiae Oeconomia*, *4*(1), 123-136.

Emekter, R., Tu, Y., Jirasakuldech, B. and Lu, M. (2015). Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending. *Applied Economics*, *47*(1), 54-70. DOI: 10.1080/00036846.2014.962222.

Falola, H. O, Salau, O. P, Olokundun, M. A, Oyafunke-Omoniyi, C. O, Ibidunni, A. S, Oludayo, O. A. (2018). Employees' intrapreneurial engagement initiatives and its influence on organisational survival. *Business: Theory and Practice*, 19, 9-16. https://doi.org/10.3846/btp.19.21576

Feller, J., Gleasure, R. and Treacy, S. (2014). Personal Transparency and Unexpected Information Sharing in Peer-to-Peer Lending Success: An Empirical Study. Journal of Information Technology. *Technology-Enabled Organizational Transparency and Openness Working Paper*, 2014-01. Available online: http://openresear.ch/wp-content/uploads/TOTO-WORKING-PAPER-2014-01.pdf. Referred on 6. 1. 2017.

Fischer, R. A. (1921). Studies in crop variation. I. An examination of the yield of dressed grain from Broadbalk. *The Journal of Agricultural Science*, *11*(2), 107-135. DOI: 10.1017/S0021859600003750.

Freedman, S. and Jin, G. Z. (2008). Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com. *Net Institute Working Paper*, 08-43. DOI: 10.2139/ssrn.1936057. Available online: http://en.ccer.edu.cn/download/6641-1.pdf. Referred on 4. 7. 2017.

Gavurova, B., Tkacova, A. and Tucek, D. (2017). Determinants of public fund´s savings formation via public procurement process. *Administratie si Management Public*, 28, 25-44.

Grčić Fabić, M., Zekić, Z. and Samaržija, L. (2016). Implementation of Management Innovation – a Precondition for the Development of Local Government Effectiveness: Evidence from Croatia. *Administration and Public Management*, 27, 7-29. Available online: http://www.ramp.ase.ro/en/_data/files/articole/2016/27-01.pdf. Referred on 23. 9. 2017.

Hagyari, P., Bačík, R. and Fedorko, R. (2016). Analysis of the key factors of reputation management in conditions of city marketing. *Polish Journal of Management Studies*, *13*(1), 69-80. DOI: 10.17512/pjms.2016.13.1.07. Available online: https://pjms.zim.pcz.pl/resources/html/article/details?id=156950. Referred on 4. 7. 2017.

Hemer, J., Schneider, U., Dornbusch, F. and Frey, S. (2011). *Crowdfunding und andere Formen informeller Mikrofinanzierung in der Projekt- und Innovationsfinanzierung*. Karlsruhe: Fraunhofer-Institut für System- und Innovationsforschung.

Herzenstein, M., Andrews, R. L., Dholakia, U. M. and Lyandres, E. (2008). *The democratization of personal consumer loans? Determinants of success in online peer-to-peer lending communities*. Available online: https://www.prosper.com/downloads/research/democratization-consumer-loans.pdf. Referred on 23. 9. 2017.

Herzenstein, M., Dholakia, U. M. and Andrews, R. L. (2011). Strategic herding behavior in peer-to-peer loan auctions. *Journal of Interactive Marketing*, *25*(1), 27-36. DOI: 10.1016/j.intmar.2010.07.001. Available online: https://www.sciencedirect.com/science/article/pii/S1094996810000435. Referred on 4. 7. 2017.

Hildebrand, T., Puri, M. and Rocholl, J. (2010). *Skin in the Game: Evidence from the Online Social Lending Market*. Available online: http://www.lse.ac.uk/fmg/events/capitalMarket/pdf/CMW10J_RochollSkinintheGame.pdf. Referred on 23. 9. 2017.

Howe, J. (2006). The rise of crowdsourcing. *Wired Magazine*. Available online: https://www.wired.com/2006/06/crowds/. Referred on 4. 7. 2017.

Jarque, C. M., Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255-259. DOI: 10.1016/0165-1765(80)90024-5.

Jonek-Kowalska, I. (2017). Coal mining in Central-East Europe in perspective of industrial risk. *Oeconomia Copernicana*, *8*(1), 131-143. DOI: https://doi.org/10.24136/oc.v8i1.9.

Jovanović, F., Milijić, N., Dimitrova, M., and Mihajlović, I. (2016). Risk Management Impact Assessment on the Success of Strategic Investment Projects: Benchmarking Among Different Sector Companies. *Acta Polytechnica Hungarica*, *13*(5), 221-241.

Kortleben, H. and Vollmar, B. H. (2012). Crowdinvesting – eine Alternative in der Gründungsfinanzierung? *Private Hochschule Göttingen Forschungspapiere*, 6, 1-60. Available online: https://www.pfh.de/fileadmin/Content/PDF/forschungspapiere/crowdinvesting-eine_alternative_in_der_gruendungsfinanzierung.pdf. Referred on 23. 9. 2017.

Kovacova, M. and Kliestik, T. (2017). Logit and Probit application for the prediction of bankruptcy in Slovak companies. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *12*(4), 775-791. DOI: 10.24136/eq.v12i4.40.

Luo, B. and Lin, Z. (2013). A decision tree model for herd behavior and empirical evidence from the online P2P lending market. *Information Systems and e-Business Management*, *11*(1), 141-160. DOI: 10.1007/s10257-011-0182-4. Available online: https://link.springer.com/article/10.1007/s10257-011-0182-4. Referred on 4. 7. 2017.

Michalski, G. (2014). *Value-Based Working Capital Management*. Palgrave Macmillan. DOI: 10.1057/9781137391834.

Michalski, G. (2016). Risk Pressure and Inventories Levels. Influence of Risk Sensitivity on Working Capital Levels. *Economic Computation and Economic Cybernetics Studies and Research, 50*(1), 189-196. Available online: http://www.ecocyb.ase.ro/nr20161/11 - Dr. Habil. Grzegorz MICHALSKI(T).pdf. Referred on 23. 9. 2017.

Petersen, M. A. (2004). Information: Hard and Soft. *Northwestern University Working Paper*, July 2004, 1-20. Available online: http://www.kellogg.northwestern.edu/faculty/petersen/htm/papers/hard%20and%20soft%20information.pdf. Referred on 4. 7. 2017.

Pindyck, R. S. and Rubinfeld, D. L. (1997). *Econometric Models and Economic Forecasts*, Boston: McGraw-Hill.

Pope, D. and Sydnor, J. (2011). What's in a picture? Evidence from Prosper.com. *Journal of Human Resources, 46*(1), 53-92. DOI: 10.1353/jhr.2011.0025. Available online: https://faculty.chicagobooth.edu/devin.pope/research/pdf/Website_Prosper.pdf. Referred on 23. 9. 2017.

Pötzsch, S. and Böhme, R. (2010). *The Role of Soft Information in Trust Building: Evidence from Online Social Lending*. Trust and Trustworthy Computing – Third International Conference 2010, 381–395. DOI: 10.1007/978-3-642-13869-0_28. Available online: https://www.wi1.uni-muenster.de/security/publications/PB2010_SoftInformation_SocialLending_TRUST.pdf. Referred on 4. 7. 2017.

Ravina, E. (2008). Love & Loans: The Effect of Beauty & Personal Characteristics in Credit Markets. *Columbia University Working Paper*, 1-77. DOI: 10.2139/ssrn.1107307. Available online: https://www0.gsb.columbia.edu/mygsb/faculty/research/pubfiles/3162/beauty_race2.pdf. Referred on 23. 9. 2017.

Sanusi, K. A., Meyer, D., Ślusarczyk, B. (2017). The relationship between changes in inflation and financial development. *Polish Journal of Management Studies, 16*(2), 253-265.

Sonenshein, S., Herzenstein, M. and Dholakia, U. M. (2011). How accounts shape lending decisions through fostering perceived trustworthiness. *Organizational Behavior and Human Decision Processes*, *115*(1), 69-84. DOI: 10.1016/j.obhdp.2010.11.009.

Szczygieł, N., Rutkowska-Podołowska M. and Michalski, G. (2015). *Information and Communication Technologies in Healthcare: Still Innovation or Reality? Innovative and Entrepreneurial Value-creating Approach in Healthcare Management*. 5th Central European Conference in Regional Science 2014, Technical University of Košice, 1020–1029. Available online: http://www3.ekf.tuke.sk/cers/files/zbornik2014/PDF/Szczygiel,%20Rutkowska,%20Michalski.pdf. Referred on 4. 7. 2017.

Žurga, G. (2017). Contemporary values in public administration and indication of their further development. *Administratie si Management Public*, (29), 108-127.

Weiss, G. N. F., Pelger, K. and Horsch, A. (2010). Mitigating Adverse Selection in P2P Lending – Empirical Evidence from Prosper.com. DOI: 10.2139/ssrn.1650774. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1650774. Referred on 23. 9. 2017.

Zheng, Y., Chen, X., and Liu, F. (2014). What Matters Most to the P2P Lending Behavior – Evidence from PPDAI.COM. *2014 International Conference on Economics and Management*, 357-361.