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Success Factors in Peer-to-Business (P2B) Crowdlending: A Predictive Approach

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ABSTRACT Peer-to-Business (P2B) crowdlending is gaining importance among companies seeking funding. However, not all projects get the same take-up by the crowd. Thus, this study aims to determine the key factors that drive non-professional investors to choose a given loan in an online environment. To this purpose, we have analyzed 243 crowdlending campaigns on October.eu platform. We have obtained a series of variables from the analyzed loans using logistic regression. Results indicate that loan amount, loan term and overall credit rating are the key predictors of non-professional lender P2B crowdlending success. These findings may be useful for predicting whether the crowd will subscribe to a loan request or not. This information would help businesses to modify specific loan characteristics (if possible) to make their loans more attractive or could even lead companies to consider a different financial option. It could also help platforms select and adapt project parameters to secure their success.

INDEX TERMS Crowdfunding, crowdlending, institutional lenders, logistic regression, non-professional lenders, peer-to-business (P2B).

I. INTRODUCTION

In recent years, businesses around the world have dealt with credit restriction from banks due to the financial crisis. In this scenario, multiple sources of alternative financing have appeared driven by new technologies and the internet. Among them, crowdfunding has gained importance for financing firms against banks [1] and venture capital [2].

Several different ways of crowdfunding can be observed on public online platforms that link entrepreneurs and backers [3], [4]. Through these platforms, a large number of investors with relatively small amounts of money can either enter as partners (equity crowdfunding) or act as lenders (crowdlending) [5]. Among those, the most popular is crowdlending [6].

Crowdlending is gaining importance due to: lower interest rates for borrowers and the low defaults rates that lenders are subject to [7]. According to the type of borrower, crowdlending is sub-classified in Peer-to-Peer (P2P) and Peer-to-Business (P2B). To date, the vast majority of the existing literature has focused on P2P [7]–[14] being anecdotal the number of studies that have focused on platforms dedicated to seeking funds for companies [15]. However, Peer-to-Business (P2B) crowdlending is playing a key role as an alternative financing for SME's fulfilling their capital needs to grow up their operations [16]. Therefore, this gap in this area is one of the main objectives of this research to contribute to filling it.

Crowdlending platforms follow similar procedures [17]. Borrowers publish their loan requests and lenders choose which one to finance based on the information shared by the borrower and the platform [18]. Factors that prompt a lender to select a loan to fund have been broadly highlighted in P2P and include: loan characteristics [10], [7], [14], borrower's financial information [8], [11], borrower's non-financial features [9], [12], [13], herd behavior among the lenders [19] and social capital [7]. It may be possible to find among these factors those useful for determining success in P2B. Nevertheless, we consider that it is necessary to seek and test P2B crowdlending's drivers due to the different nature of the borrower, which affects the lending decision.

This study analyzes data obtained from October (before known as Lendix) European P2B platform. This marketplace facilitates loans between €30k and €5m for companies operating in France, Italy, and Spain. We examine the

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characteristics of 243 credits requested during the period from April 2015 to October 2017 to determine the factors that drive lenders to choose a given project.

Among the main contributions of this study, we consider that our results could be useful for borrowers to predict whether their loan request will be taken up by a large number of lenders or not. Alternatively, they could help them to design their loan request in a previous step, in a way that let them be more confident that it will be successful. They could also help the platform select and fit the loan request to ensure that it succeeds. The rest of the paper follows this structure: section 2 provides a literature review, the methodology will be broadly discussed in section 3. Then, results and discussion are given in section 4. This research finishes with a series of conclusions and implications.

II. LITERATURE REVIEW

Crowdlending is a new online financial channel that directly links borrowers to lenders. With the growth of the volume of e-commerce and the expansion of the online community, peer-to-peer lending has gained popularity as an alternative to the traditional banking system. According to Wang and Greiner [20], there are several reasons for the acceptance of online lending: first, this marketplace offers lower transaction costs for both lenders and borrowers, and enables smaller loans to be made; second, it provides a diversifying mechanism for investors. Although that, the risk factors associated with online lending should also be considered. Despite the benefits of online loans, this market suffers from a high degree of information asymmetry, which is a significant problem for market efficiency. This asymmetry exposes lenders to risk when deciding whom to finance.

It is important to note that trust plays a central role in Peer-to-Peer (P2P) lending as lenders and borrowers are not able to communicate face-to-face, and fund trading is conducted online. Hence, the only information that lenders have about the borrowers is the one published on the platform. Thus, for a sample of 1,500 lenders on the PPDai lending platform, Chen *et al.* [17] show that trust in borrowers and intermediaries are significant factors that influence lender decisions. The vast majority of prior studies has been focused on P2P lending, and mainly analyzes critical factors for the funding success of a loan, and a theoretical framework was developed by Moreno-Moreno *et al.* [21] identifying several types of success factors in crowdlending. Among these factors, the literature has found that loan characteristics are a significant determinant of funding success. The features of the listed loans, such as the interest rate, the loan amount, and the loan period, are essential factors relevant to the lenders' investment decision because they are the significant determinants of the profit that will be generated by their investments. For example, a higher interest rate offered by the listed loan can make a higher return to the lenders, so they are likely to bid for that loan. However, a higher interest rate might also be interpreted as a sign of a riskier investment. Especially in a market with a high degree of information asymmetry so that the lenders might be less interested in loans with higher interest rates [14].

According to Feng *et al.* [10], loan amount request can also determine its attractiveness since many lenders would prefer smaller loans to larger loans for risk management purposes. Lenders might also prefer shorter loan periods since this allows better liquidity. Liquidity can be a particularly critical issue in the online lending market considering many lenders are individuals rather than financial institutions. Lin *et al.* [7] show that it is difficult for more extended period loans to get fully funded.

Another factor that impacts funding success is the borrower's credit/financial information and borrowing history. In this regard, credit information provided by borrowers becomes a key factor for funding success. Freedman and Jin [11] provide evidence that the funding rate on Prosper.com increased when the site began to encourage more financial information from borrowers. Adams *et al.* [8] state that data such as credit ratings also help to mitigate adverse choices. In this line, using data from popfunding.com, Yum *et al.* [14] conclude that a good borrowing history has a strong effect on the success rate. In other line, Kgoroedira *et al.* [22] established that company information is not relevant in lenders decision.

Researchers have also focused on the role of physical appearance, gender, age and race in marketplace P2P lending. For example, Duarte *et al.* [9], Pope and Sydnor [12] and Ravina [13] find that female borrower have a higher likelihood of funding success and pay lower interest rates [12]. Herzenstein *et al.* [19] find those female borrowers have lower default rates. However, Barasinska and Schäfer [23] find no evidence that female borrowers have a better chance of obtaining funding.

Other researchers have been interested in investigating the project description of the proposed loans. Lin *et al.* [7] find that an extensive loan description with shorter sentences has a positive effect on funding success. In the same research line, investigating two German portals—Auxmoney and Smava—, Dorfleitner *et al.* [24] find that spelling errors, text length and keywords evoke positive emotions that predict funding success.

Herd behavior has also been observed in the lending marketplace. Herzenstein *et al.* [19] show that strategic herding takes place in marketplace lending. In particular, they reveal that a 1% increase in bids increases the likelihood of additional requests by 15%.

Finally, social capital and friendship have also been studied as success factors for loan funding in P2P. Lin *et al.* [7] investigate the funding process linked to online friendship networks on Prosper.com. These authors find that these friendship networks reduce the likelihood that a loan will not be funded, lower the interest rates being paid, and are correlated with lower default rates of the loan later on.

As P2P crowdfunding has grown, new modalities have appeared, where Peer-to Business (P2B) becomes one of the most relevant. One of the biggest challenges faced by firms is funds-obtaining. Traditionally, financial intermediaries, such as banks, venture capital firms, and angel investors, used to provide firms with funds, but the financial crisis brought economic woes as the traditional financing channels dried up, especially for small firms [25]. In this context, crowdfunding emerged as a real alternative for funding entrepreneurs directly, even with small amounts. The crowd (the mass of individuals) provides financial resources to the entrepreneur in return for equity stakes or interest rate.

Online platforms facilitate the connection between the crowd and the firms. The borrowers post the amount of money they wish to borrow, and the interest rate they intend to pay for the loan on the website. Borrowers also share their financial information, so lenders have more details to decide whether or not to contribute to their project. However, sometimes this information is not enough as lenders extending credit to small businesses on P2B websites are not experts in assessing credit risk. Regarding this, most of the platforms give companies credit scores added to the information given by the borrowers themselves in order to mitigate information asymmetries. They also set the interest rate for the loan in many cases.

As these marketplaces for Small and Medium Enterprises (SMEs) have become more popular, researchers have focused on them and the factors driving funding success. However, the amount of literature is still scarce. Previous P2P-based literature might not apply when examining marketplace lending for SMEs since the individual decision to fund a firm might be driven by a different rationale than those applicable to fund a personal loan.

In the case of P2B, research must focus on the companies' financial disclosures, the ratings offered by the platforms and the impact of the loan characteristics set by the platform. Cumming and Hornuf [15] examine these questions using data from the largest SME marketplace in Germany (Zencap) and conclude that information provided by the platform (rating) seems to play a critical role in funding success, while lenders pay much less attention to company financial variables, such as income, assets, and liabilities. Kgoroeadira *et al.* [26] examine the online platform Prosper.com and conclude that lenders focus on borrowers' characteristics and ignore business characteristics.

Following this research line, the objective of our study is to shed light on key factors that drive non-professional investors to choose a given project from a predictive approach. For this, we have taken as essential factors them that have been proven to influence both P2P and P2B funding success in the literature. Specifically, our study tests borrower factors, loan characteristics and variables offered by the online platform.

III. METHODOLOGY

This study analyzes 243 crowdlending campaigns on the October platform. We obtained a set of data related to the loans, which were subsequently analyzed using logistic regression with the backward stepwise method in order to highlight key factors for lenders. Binary logistic regression was chosen because it is a suitable technique for examining the relationship between a categorical response variable and one or more categorical or continuous predictor variables. This type of analysis has long been used in other research on finance and lending [14].

The R statistics software [27] has been used to obtain the results with specific use made of Base, CARET package [28] and RMS package [29] functions for predictive model calculations.

A. DATA SOURCE

1) PLATFORM DESCRIPTION

October is a platform registered in France which currently operates in Spain and Italy too. Several types of investor can operate on this platform: private and institutional or professional investors. Firstly, professional and institutional investors (including Family Offices) automatically invest 51% in all projects through a debt fund, leaving the remaining amount for private investors. When private investors do not finance the remaining 49%, the fund is obliged to complete the project up to 100%. This particularity of the platform means that it is not possible to identify failed loan requests. However, loans that need to be completed by institutional investors seem to be less attractive for a private investor to the crowd as they do not get the supporting of the crowd.

However, private investors can invest in a variety of projects on the platform. Each project presents information about the company, such as age, number of employees, customer portfolio and information about the management team. It also provides the company's financial statements. Moreover, there is information about the requested loan: its purpose, maturity and interest rate. The latter is determined by the rating given by the platform's credit team and is based on an analysis of the company's financial data. October also provides the opinion of the analyst who studied the loan operation and performed the financial analysis of the company in the project file.

In this study, we aim to determine, among a set of variables provided by the platform, which factors are significant for predicting loans that will need to be oversubscribed by professional investors. To this purpose, we separate loans funded by institutional investors at the lower level (51% of the total loan amount) [Loans More Attractive for private Investors - LMA] from those that needed to be completed at the end of the subscription period (with more than 51% of Institutional Investors loan share percentage) [Loans Less Attractive for private Investors - LLA]. Then, we analyze the different factors available on the platform that induce the crowd to loan to a project. Our data consist of 243 loans being sought, listed on October from April 2015 to October 2017.

2) VARIABLE DESCRIPTION

Given our aim in this study, we use as response variable the percentage of loan amount subscribed by institutional

TABLE 1. Variable descriptions and summary statistics.

			LFQ=FALSE	LFQ=TRUE
	TOTAL (n=243)		LMA (n=135)	LLA (n=108)
Variable Description	mean	St.dev	mean	mean
Borrower factors				
Shared Capital (€)	1499336.0	4702251	205169.7	2534668.2
Company age (years)	15.6	13.58	13.6	17.2
Loan characteristics				
Loan Term (months)	48.8	16.15	45.6	51.3
Loan Amount (€)	373799.1	465708	115890.7	580125.9
Loan Rate (%)	6.8	1.22	7.2	6.4
Variables provided by OCTOBER				
Overall score	1.8	0.61	1.6	2.1
Financial health score	2.2	0.76	2.1	2.2
Company track record score	2.7	0.63	2.6	2.8
Profitability score	1.5	0.73	1.4	1.6
Response variable and other results of funding process				
% Institutional investors (%)	**66.7**	**16.95**	**51.0**	**79.2**
Number of lenders (people)	582.6	452.31	476.3	667.6
Funding term (hours)	120.0	154.2	21.2	199.0

Score variables at October take A, B, C values, being A the best score and C the worst. For our analysis, these have been transformed into discrete numeric variables as follows: C=1, B=2, and A=3.

investors (% Institutional investors, see Table 1), which values within a range of 51%-100%. When studying the dataset in an exploratory manner, significant different behaviors of the variables in the two groups were found, depending on whether Institutional Investors have subscribed for more than 51% of the loan amount (LLA) or for precisely 51% (LMA), which, as stated previously, is the minimum level of investment allowed for investors of this type (see Table 1).

As the two identified groups fulfil a condition, one new variable labelled ''Loan funded by Qualified and Institutional Investors'' (LFQ) can be dummy coded as follows:

If Institutional Investors do not subscribe over 51% of the loan amount [LMA], the dummy variable takes a value of FALSE. On this case, the loan was backed for private investors.

Otherwise (when there is a higher percentage of the loan amount in Institutional Investors' hands) [LLA], the dummy variable takes a value of TRUE.

This new dependent (binary) variable will be used to fit our model. Summarizing:

LFQ = FALSE -> The loan will be considered as LMA.

LFQ = TRUE -> The loan will be considered as LLA.

Two variables, Funding Term and Number of Lenders, will not be included in the analysis because of their high correlation with our response variable. It could be said that they are an outcome of the funding process. As we aim to conduct predictive analysis, we must use ex-ante variables. However, several independent variables were analyzed to predict the group in which the loan request should be included (Table 1). First, related to borrowers, factors such as financial information linked to their share capital and Company age were studied. Feng *et al*. [10] pointed out that this kind of information is key to a loan request being successful. In our data set, the group of older companies and companies with higher shared capital means (Table 1) seem to receive more finance from institutional investors [LLA].

Three variables have been analyzed concerning loan characteristics: rate, amount and term. Although a high-interest rate is related to a risky loan [14], our data show that projects with a higher rate are less likely to need institutional investors [LMA]. Additionally, many lenders would prefer smaller loans to larger loans for risk management purposes [10] and this is confirmed in our dataset as the less institutional investment group [LMA] presents a much lower loan amount mean (€115,890) than the institutional investment group [LLA] (€580,125). Moreover, as Lin *et al.* [7] state, it is more difficult for more extended period loans to get fully funded. This idea is in line with our dataset, which shows a higher mean loan term in the LLA group (51.27 months) than in the LMA group (45.64 months).

As crowdlending carries risk, it is essential to identify credible borrowers and choose the right lending intermediary [17]. As a result, most lenders base their investment strategy on the credit risk analysis provided by the platform. In this particular case, October analyzes every project before its publication on the platform. This analysis enables the loan request to be labelled as (order from best to worst) A+, A, B+, B or C depending on information about the company's financial health, profitability and history. An overall score is given by combining these three factors. Finally, the higher the rating, the lower the loan interest rate. It is not surprising that the less institutional investment group [LMA] presents the most inferior rating as this is in line with the higher loan rate mean that this group also presents. The following section analyzes the data further and presents the statistical methodology applied to the commented data set.

B. RESEARCH METHODOLOGY

As stated previously, this study seeks to determine factors that are significant for predicting loans that will need to be oversubscribed by professional investors. Binary Logistic regression (LR) has been used to obtain a predictive model based on our dataset. This methodology is appropriate for the analysis as our objective is to determine key aspects that lead to successful campaigns and, as has been stated previously, as we are working with a dichotomous dependent variable. We have chosen binary logistic regression because it is a suitable technique for examining the relationship between a categorical response variable and one or more categorical or continuous predictor variables.

Before we can conduct the LR, we must first centre and scale (standardize) the dataset due to the significant differences in the scales of some of the variables, as shown when comparing their ranges in Table 1. In addition, we divide the data into training (80%: 195 samples) and testing (20%: 48 samples) random datasets. All the following analysis will be carried out on the training dataset, with the testing dataset used at the end to assess prediction capability.

Furthermore, to make the model as simple as possible, we use an AIC (Akaike Information Criterion)-based backward stepwise method [30] to reduce the number of variables. This method starts the analysis with all of the variables, removing them one by one if they contribute insufficient information to the model. Variables significant at 95% confidence level will comprise our optimum model.

The previously obtained optimum model is put through repeated k-folded cross-validation (three repetitions and ten folds) to fine-tune to secure a reliably accurate figure, independently of the specific training and testing subsets. That is a robust method for estimating classification accuracy and reducing the amount of bias in the estimate [31]–[35].

Finally, the fitted model is checked against the testing dataset to generate the confusion matrix. This result is useful to check whether the model is producing types of errors that are balanced. This technique summarizes the performance of a classification algorithm. Classification accuracy alone can be misleading if there is an unequal number of observations in each class or if there are more than two classes in the dataset. Calculating a confusion matrix provides information about what the model is doing correctly and what types of errors are making. In the following section, the results are examined.

IV. RESULTS AND DISCUSSION

This analysis shows that the variables that are significant at a confidence level of at least 95% are Loan Term, Loan amount and Overall Score, which comprise our optimum model. Table 2 sets out the results obtained with the employed methodology. However, not all of the variables in Table 1 are included in the regression equation for the reasons described in the backward stepwise method explained above. Nevertheless, it is important to focus on the significance obtained for the variables to determine whether they are essential for our investigation. Two variables (Loan Amount and Overall Score) have a significance of at least 99.9% and one (Loan Term) a confidence level of at least 95%. These significance levels show that the selected variables are relevant to the model fit.

As can be seen in Table 2, the estimated coefficients are positive. Thus, their relationship is direct. The increase or decrease of every variable is similar to the outcome variable. However, the specific estimated coefficient values cannot be interpreted as they belong to a LOGIT model and the sample values have been standardized before fitting.

A. FITTED MODEL FORMULA

The dependent variable in our model is Loan funded by Qualified and Institutional Investors. Given our LR model, LFQ will be a dichotomous variable that can take the following two values: [LMA] FALSE (=0) and [LLA] TRUE (=1). TRUE if the estimated logistic probability exceeds 0.4999 and FALSE otherwise.

The rest of the estimated coefficients for the independent variables in the logit function take the values in Table 2. Hence, the estimated logit function is given by the following expression:

TABLE 2. Adjusted logistic regression coefficients.

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.81	0.45	4.06	4.86e-05 ***
Loan Term	0.60	0.26	2.26	0.0238 *
Loan Amount	4.95	0.93	5.31	1.09e-07 ***
Overall Score	1.18	0.26	4.52	6.21e-06 ***

Significance *** < 0.001; ** < 0.01; * < 0.05
*** significant at a confidence level of at least 99.9%
* significant at a confidence level of at least 95%

LFQ(x) = 1.8086 + 0.5978 Loan Term + 4.9486 Loan Amount + 1.1816 Overall Score

Once the fitted model is obtained, we proceed with the repeated k-folded cross-validation (ten folds, repeated three times) to adjust the accuracy figure independently of the sample and to reduce the estimation bias. The training sample consists of 195 examples. An accuracy of 0.8423392 (84.23%) is achieved with this resampling method. This figure can be considered a very good fit (>70%), as it is obtained by calculating the mean of the accuracy statistics given by all the cross-validations in the sample. Some functions in the CARET package (Kuhn, 2008) were used to obtain the value.

B. MODEL ASSESSMENT

Together with the adjust parameters, the primary procedure used to assess LR predictive models is the confusion matrix (Table 3). This instrument allows us to check if predictions are balanced while also provides an overall idea of the power of the achieved fit. In our case, [LMA] is FALSE (Institutional Investors do not take over 51% of the loan amount) and [LLA] is TRUE.

TABLE 3. Confusion matrix.

	Reference	
	FALSE	TRUE
FALSE	20	6
TRUE	1	21
	21 = 43.75%	27 = 56.25%

Accuracy: 0.8542
95% CI: (0.7224, 0.9393)

Confusion matrix results are well balanced for all the groups. An outstanding accuracy ratio is also obtained for the TEST sample (48 samples): 0.8542 (85.42%). It could be stated that the model is more finely tuned to LMA projects, for which the sensitivity value is 0.9524, whereas the specificity value is 0.7778 (success ratio with LLA projects)

C. DISCUSSION AND CONCLUSIONS

The purpose of the present study is to provide a model that helps to predict which crowdlending projects would receive higher take-up by non-institutional investors. To do so, we have considered factors such as loan amount, loan term and overall score (credit-scoring) provided by the platform. We have observed that Investors seem to prefer smaller loan amounts, shorter loan terms, and are influenced by the financial information score that the platform provides.

These results obtained are accurate (reliable) and more than acceptably consistent. First, our results noted that only three out of the nine studied variables (see Table 1) have significance levels above 95% and so these are the ones used in the fitted model formula (Table 2).

Of those that were not significant, we can highlight Loan Rate, which Yum *et al.* [14] linked directly to risk levels. It must, therefore, be linked to a lesser likelihood of success in the campaign to secure funding. However, we found that investors prefer to finance projects with higher loan rates, which could indicate a differentiating factor between P2B and P2P. It may also indicate a greater preference for risk in search of higher returns.

There is a group of variables that are scores provided by the platform. These variables are analyzed by Cumming and Hornuf [15], these authors found that profitability, financial health and the company history (financial variables) were not significant, whereas the overall score (information provided by the platform) was.

Factors in the Borrower group are not significant, either. This result is in line with the above authors but also contradicts to some extent what Barasinska and Schäfer [23] state about lender interest in borrowers' characteristics. That could be another differentiating feature between P2B and P2P.

Focusing on the significant variables in our model, what Feng *et al.* [10] indicated - the higher the Loan Amount, the smaller the likelihood of crowdlending projects being successful - is consistent with our results. Besides, descriptive results in Table 1 indicate that the mean Loan Amount of successful projects was approx. €116,000 compared to a mean well above €580,000 for projects that required institutional funding.

Also, our results are significant and consistent about the Loan Term (Period). The relationship of this variable and a successful funding campaign coincides with what was stated in Lin *et al.* [7]: shorter loan periods are related to greater success. Moreover, results also indicate the investor's preference for liquidity.

Finally, there are several studies [8], [11], [14] in which a greater level of borrower financial information as knowledge of the borrower's track record is related to a higher likelihood of success. In our case, we have used four aggregates provided by the platform. One of these, the overall score (OS) is, in turn, an aggregate of the other three and is significant. Our study indicates that the better the OS, the less the likelihood of being successful (i.e., successfully financed by non–institutional investors). This may indicate that investors seek projects with greater risk (lower OS) in exchange for higher profitability. Table 1 shows that the mean loan rate for successful cases is 7.19%, whereas, for all others, it is 6.4%. Another possible interpretation could be that the nature of crowdlending (small amounts can be invested in different projects) results in a diversification strategy that allows tolerating higher levels of risk. This interpretation is in the same line as studies mentioned above and it is also consistent with the prior literature. In fact, the success group (LMA) in our study has lower overall score ratios than the fail group (LLA).

D. LIMITATIONS

Before the conclusions that can be drawn from our study, it should be indicated that there are some aspects in the literature review that could not be evaluated or compared for a variety of reasons.

Specifically, Duarte *et al.* [9], Pope and Sydnor [12], and Ravina [13] address the influence of aspects such as physical appearance, gender, age and race in marketplace P2P lending. Studying aspects such as personal behavior, Herzenstein *et al.* [19] and Barasinska and Schäfer [23] found that female borrowers have lower default rates. As we study company profiles and investment projects, these types of variables are not applicable, and we do not have any variables related to those previously mentioned. We can observe critical differences between P2B and P2P in this aspect.

Certain aspects could not be verified due to the lack of these or other related variables in our database, including herd behavior [19], the effect of social capital and friendship networks [7] and the effect of the loan description on funding success [24], [7].

E. SCIENTIFIC IMPLICATIONS

Some of our findings represent a significant extension to the prior literature by broadening studies that were focused solely on P2P aspects. In some cases, a company loan is treated as if it were P2P. In light of our results, we believe that specific treatment of this type of loans is required, as we consider that the investor in P2B frequently pursues other goals, or uses different reasoning with regard to risk assumption and profitability requirements. The fact that the investment is online through a marketplace does not imply that the characteristics of the investors are the same. Platforms can be observed to be seeking market segmentation by targeting lenders with particular risk, term and profitability objectives.

F. MANAGERIAL IMPLICATIONS

Our results could be helpful for both companies and funding platforms, in the sense that they might be useful for making optimal decisions about the characteristics of the projects proposed to investors. Platforms would be able to adapt their projects in such a way as to achieve higher levels of success among their investors. On the company side, it may help firms to seek loans with characteristics that they know beforehand will have a greater likelihood of finding success with the investors that they are addressing on this type of platform.

G. FUTURE RESEARCH

From our point-of-view, it would be interesting to address the following:

First, there should be a verification that results of new lending projects on October continue to comply with those of this study. A new fit should even be made based on a more significant number of observations, as this would provide the model with greater robustness. Second, it would be essential to verify whether the obtained results can be extrapolated to other similar platforms. In this case, the number of projects has limited model validation and web accessibility to information about relevant variables for analysis. In addition, it would be an interesting line of future research to analyze the role of public investor in P2B lending.

Similarly, it would be interesting to propose this methodology for the analysis of other funding sources via online platforms (equity) to be able to compare the profile of other investors and gauge the opportunities that it provides for companies and the platforms themselves.

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