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The use of profit scoring as an alternative to credit scoring systems in peer-to-peer (P2P) lending

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Abstract

This study goes beyond peer-to-peer (P2P) lending credit scoring systems by proposing a profit scoring. Credit scoring systems estimate loan default probability. Although failed borrowers do not reimburse the entire loan, certain amounts may be recovered. Moreover, the riskiest types of loans possess a high probability of default, but they also pay high interest rates that can compensate for delinquent loans. Unlike prior studies, which generally seek to determine the probability of default, we focus on predicting the expected profitability of investing in P2P loans, measured by the internal rate of return. Overall, 40,901 P2P loans are examined in this study. Factors that determine loan profitability are analyzed, finding that these factors differ from factors that determine the probability of default. The results show that P2P lending is not currently a fully efficient market. This means that data mining techniques are able to identify the most profitable loans, or in financial jargon, "beat the market". In the analyzed sample, it is found that a lender selecting loans by applying a profit scoring system using multivariate regression outperforms the results obtained by using a traditional credit scoring system, based on logistic regression.

Keywords: P2P lending, microcredit, crowdfunding, banking, interest rates, credit scoring, profit scoring, decision trees, internal rate of return.

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1. Introduction

Credit scoring poses a classification problem in that the dependent variable is dichotomous and assigns “0” to failed loans and “1” to non-failed loans. Subsequently, techniques such as logistic regression or neural networks try to estimate the borrower’s probability of default (PD). For lenders, not only does the PD matter but also the profit gain which the loan is likely to produce. This profit gain also depends on the loss given default (the share of a loan that is lost when a borrower defaults) and on the interest rate charged [1]. Factors explaining the PD may differ from those factors explaining profits. For example, the PD of startup business loans may be higher than the PD of wedding loans; however, if a startup business loan’s interest rate is high enough, the profits from lending to entrepreneurs may be even greater than the profits from lending for weddings. Factors explaining the PD are well known: Abdou and Pointon [2] and Lessmann et al. [3] review recent studies. However, few studies analyze the factors explaining loan profitability. This is caused by the difficulty of calculating customer profitability and the lack of necessary data [4]. The goal of this study is to develop a profit scoring Decision Support System (DSS) for investing in P2P lending.

The P2P lending market is made up of individual lenders that provide loans to individual borrowers using an electronic platform. This platform puts lenders in contact with borrowers by charging a fee. Lenders bear the full risk of this operation. Recent studies develop P2P credit scoring [5, 6, 7], although none propose profit scoring. A profit scoring DSS allows for selection of the most profitable borrowers, which is related to customer lifetime value [8]. The calculation of customer profitability for a store selling products on credit requires data from the management accounting system, such as the margin of each product sold to each customer. For financial institutions, each customer may own different products, ranging from mortgages to credit cards, and may use different channels, ranging from bank branches to online banking. All of these combined factors make it difficult to obtain precise data on customer profitability, and researchers complain about the lack of enough data to investigate profit scoring [3]. However, P2P lending platforms provide sufficient data; this is because P2P lending suffers from a severe problem of information asymmetry –lenders know little of borrowers and normally would not lend to them [9], and P2P platforms try to cope with this lack of data by disclosing as much information on borrowers as they can provide, including loan payments. Furthermore, the P2P business model is considerably leaner than the bank business model. Hence, it is feasible to calculate relevant borrower profitability measures.

This study proposes utilizing the internal rate of return (IRR) of each loan as a profitability measure. IRR is a well-known financial formula that may be easily computed for investments that have an initial cash outflow (the loan amount) followed by several cash inflows (the payments), and may contain irregular repayment schedules [10]. In the loans market, the IRR is the lender's effective interest rate, which may differ from the borrower's effective interest rate, due to delinquent loans and fees. The use of IRR has two advantages. First, IRR is a continuous variable that allows more precise information when compared to a dichotomous variable. Take, for example, three borrowers obtaining a $100 loan at a 10% interest rate: the first borrower pays back $110, the second borrower pays $102 and the third borrower pays back $5. The first loan is fully paid, while the second and third loans are considered as charged off, although the second borrower has paid most of the payments. In fact, the first loan's IRR is 10%, the second loan's is 2% and the third loan's is -95%. The second advantage is that IRR takes into account not only loan payments, but loan interest rates. The riskiest loans have a high PD but also offer lenders high interest rates to compensate them for this high PD. An example is microcredits, loans to financially excluded people, which may be risky but profitable, given their high interest rates [11].

The first research question addressed in this study is methodological and deals with the design of a profit scoring DSS for P2P lending, which is the main contribution of this study. Other studies develop profit scoring for credit cards and consumer credit [12, 13, 14, 15, 16, 3]; however, the lack of data resulted in the use of customer profit proxies. To the best of our knowledge, there are no previous studies using the IRR as a dependent variable. The proposed methodology of this study combines exploratory analysis, multivariate regression and CHAID, a decision tree technique [17].

Conventional credit scoring models seek to determine factors explaining loan reimbursement, although these factors may differ from factors explaining loan profitability. It is acknowledged in prior studies that business loans are riskier than car loans [7]; the effect of borrower's annual income on the PD is well-known [18], as is the relationship between credit history and PD [19]. However, the determinants of profitability have yet to be systematically studied. The second research question investigates the factors explaining profitability in P2P lending.

P2P lending is an electronic marketplace where borrowers request money and lenders select appropriate borrowers. A market in which prices always fully reflect available information is called efficient [20]. If the P2P loan market is efficient, its prices (loan interest rates) will reflect all available information. Hence, a particular lender will be unable to obtain positive abnormal returns by selecting borrowers because this information is already contained in the prices. The efficient-market hypothesis states that it is impossible to "beat the market" [21]. Although this concept originally applied to stock markets, it may adapt to other markets, such as the labor market [22] or the credit market [23]. The third research question tests the efficiency of the P2P loan market. If this market is efficient, the strategy followed by a particular lender is irrelevant because profitability will be identical.

This empirical study utilizes data from the Lending Club, the largest U.S. P2P lending platform. The sample contains 40,901 loans, of which 4,800 are failed. Intertemporal cross-validation is utilized as a validation method: the train sample contains all available loans up to a given date, while the test sample contains all available loans after this given date. Our study shows that the borrower's rate of interest, borrower's indebtedness, and loan purpose are all factors explaining the IRR, although the relationship is not linear. The use of decision trees allows detecting useful rules for investors. Beyond credit scoring, this study encourages the use of IRR as a dependent variable and further research into new approaches to develop profit scoring systems. Therefore, efficiency of this market will be further improved.

The remainder of the paper is organized as follows: section two summarizes the relevant previous studies on profit scoring and on P2P lending. Section three presents the empirical results of the analyses. Section four discusses the results from the previous section, offering practical implications, scholarly contributions, limitations of the study, and future directions. Section five concludes with a summary.

2. Literature review

Credit scoring systems seek to estimate the PD based on statistical models, such as logistic regression [24], neural networks [25] or support vector machines [26]. Statistical scoring models have focused primarily on the minimization of default rates, which is only one of the dimensions of the more general problem of granting credit, as warned by Eisenbeis [27]. Credit lenders seek to change the focus from minimizing the risk of a borrower defaulting to maximizing the profit a borrower provides [19]. This author presents four approaches to develop a profit scoring system. The first approach is to build on the existing credit scorecards and attempt to define profit for groups of the population segmented according to their scores. Another approach is to build on the Markov chain approaches to develop more precise models. The third approach utilizes survival analysis to estimate profit obtained from a borrower. The final approach mimics the regression approach of credit scoring by attempting to define profit as a linear function of the independent variables. This is the most frequently used approach and is the approach utilized in this study, but using non-linear multivariate regression and by means of the CHAID algorithm. Decision makers need tools that are able to accurately predict loan defaults; however, they also seek to model loan default symptoms by identifying relevant variables. Multivariate regression is the standard tool that is widely used as a benchmark, while decision trees, such as CHAID produce rules easy to interpret and implement; which is why they were selected for this analysis.

Table 1 indicates a revision in prior studies regarding profit scoring. To the best of our knowledge, there is no previous research using IRR as a dependent variable in the P2P context. Lessmann et al. [3] benchmark state-of-the-art algorithms for both credit and profit scoring. These scholars claim that profit scoring development is difficult because data sets lack specific information related to time and data regarding the loss given default. These scholars employ a simpler approach to estimate scorecard profitability by examining classification errors costs, as suggested by Eisenbeis [27]. This is the most frequent procedure; at least, it provides a rough estimate of the financial rewards. Finlay [28] and Finlay [12] develop credit scoring for profitability objectives. These scholars apply credit scoring to a large UK catalogue retailer that provides revolving credit. Credit is provided interest free and the profit from each account was calculated as net revenue minus bad debt. This measure is a proxy for customer value and is also used by Andreeva et al. [29]. Barrios et al. [14] utilized the cumulative profit relative to the outstanding debt for scoring purposes. They recognize the limitations of using this proxy because a standard accounting return requires a more detailed allocation of the total assets used by each customer. They apply their model to the case of consumer revolving credit and identify specific segments of customers that are profitable in relative terms.

**** Table 1 ****

Verbraken et al. [15] develop a profit-based classification performance measure for credit scoring. This measure accounts for profits generated by solvent loans and expenses created by failed loans. They report that using this measure for model selection leads to more profitable credit scoring models. Stewart [13] proposes another profit-based scoring system for credit cards and reports that borrowers most likely to charge-off are also more likely to spend on their cards, pay finance charges and pay fees. So et al. [16] develop a profitability scoring model for credit card users including revolver assessments. The approach is similar to the standard method in predicting default but it is more accurate in estimating the profitability of potential applicants.

Bachmann et al. [30] and Bouncken et al. [31] review recent studies on P2P lending. One of the first empirical studies on P2P lending is Berger and Gleisner [32] who analyze the role of intermediaries in electronic markets using data of 14,000 loans from a P2P lending platform. They explain how electronic credit markets operate, and provide insights into the role of intermediaries in the marketplace. Guo et al. [6] expand on Berger and Gleisner's study and develop a credit scoring model using kernel regression. Emekter et al. [33] propose a credit scoring model for P2P lending, based on survival analysis. They demonstrate that credit grade, debt-to-income ratio, FICO score and revolving line utilization all have important roles in loan defaults.

3. Empirical study

3.1 Sample and data

This empirical study utilizes Lending Club data. Lending Club is the largest U.S. P2P loan platform in number of loans and was the first P2P platform to offer public stock in the New York Stock Exchange Market. Lending Club collects borrower information including annual income and loan purpose. Lending Club also provides information about the borrower's credit history and FICO score which is obtained from the Fair Isaac Corporation. From these data, Lending Club assigns a grade to each loan and determines the interest rate. All borrower information is available on the

Lending Club webpage, as well as payments made in each time period[1]. The Lending Club website provides information from 2007. However, Lending Club's loans in 2007 were discarded because they were issued under the company's pilot credit model. The minimum loan term is 36 months. For this reason, only loans issued up to June 2012 were utilized because subsequent loans are still outstanding and their IRR cannot be calculated. 40,901loans were analyzed. Out of this total, 4,800 are failed (11.74%) and 36,101 are non-failed (88.26%).

3.2 Variables

Table 2 displays the study variables. The monthly principal amount and interest payments are utilized to calculate IRR, the dependent variable. Delinquent loans are occasionally recovered and recovery fees apply if litigation ensues. Because certain payments are delayed and certain loans are terminated early, these payments are neither periodic nor uniform. However, Lending Club provides data on real payments with their payment dates which allows for easy calculation of the IRR by using the XIRR function in any spreadsheet software.

**** Table 2 ****

Dependent variables are borrower assessment variables such as grade, subgrade, FICO score and the borrower's interest rate. Loan characteristics include loan amount and loan purpose; 14 loan purposes exist, including wedding, small business, and automobiles, among others. Borrower characteristics include annual income, housing situation and length of employment. Credit history is measured with variables including the number of delinquency incidences and types of credit used. Finally, borrower indebtedness is measured with three ratios relating debt, annual instalment and loan amount to annual income.

[1] Data are located in two different tables: borrowers' data can be found at https://www.lendingclub.com/info/download-data.action and payments' data can be found at http://additionalstatistics.lendingclub.com, so it is necessary to join both tables.

3.3 Exploratory analysis

The first analysis is exploratory. Figure 1 displays the loan's IRR histogram; IRR does not follow a normal but rather an asymmetrical distribution. This skewed distribution is caused by defaulted loans at the extreme of the distribution tail, and results in negative IRR values. The mean IRR is 3.92% and the median is 11.22%. This skewed distribution leads to careful data analysis, considering both mean and median. Table 3 provides a cross tabulation of categorical variables. The first column indicates the number of loans for each category according to the grade, the loan purpose and the housing situation. Most loans are noted in the most solvent categories; 32.33% are "A grade" loans and 33.60% are "B grade" loans. The most frequent loan purpose is debt consolidation (47.82%), followed by credit card (16.38%). The most frequent housing situation is rent (51.15%) and mortgage (40.96%). Subsequent columns indicate the percentage of defaulted loans in each category. PD increases when grade decreases, thus, 6.28% of "A grade" loans failed, compared to 33.87% of "G grade" loans. As for loan purpose, the less risky loan purposes are major purchases and include wedding, automobile, credit card and home improvement loans, and resulted in failed loans percentages less than 10% compared to 20.44% for small business loans. The less risky housing situation reported by borrowers is mortgage, with 10.28% failed loans compared to 17.39% of "other". The next column indicates the results of a Chi2 test that reports statistically significant differences in most of the previous results. However, there is not a strong association between the independent variables and the PD, as indicated by the Phi correlation values, which are very low.

**** Figure 1 ****

**** Table 3 ****

The following columns in Table 3 demonstrate the relationship between the borrowers' interest rate and the independent variables. The borrower's interest rate follows a normal distribution; the mean is 11.33%, and the median is 11.36%. There is a linear relationship between grade and interest rate because Lending Club sets the interest rate according to the grade. “A grade” loans pay, on average, 7.42% and “G grade” loans 21.03%, which results in a 13.61 gap. The results of a means test indicates that differences are statistically significant. In regards to loan purpose, differences are also statistically significant, but the gap is smaller because car loans pay 9.76% on average, while small business loans pay 11.85% on average. As expected, it becomes clear that as PD increases, the borrower’s interest rate also increases. However, certain inconsistences arise. For example, the credit card interest rate is 11.38% and its PD is 9.29%, although renewable energy loans pay lower interest rates of 10.63% with a higher PD of 19.32%. The gap is very small in housing situation, 10.86% for mortgage and 11.93% for “other situation”, although the differences are statistically significant.

Previous results are useful to build credit scoring; however, this study focuses on profit scoring. The subsequent columns in the Table show the relationship between IRR and the independent variables. The relationship between grade and IRR appear to be complex: the most profitable loans are “B grade” loans, with a 4.33% IRR. The least profitable loans possess a lower grade; thus the IRR for “F grade” loans is 2.15%, and even negative profitability arises in “G grade” loans at -2.80%. However, the profitability of “A grade” loans is 3.79% which is less than “B grade” loans. The relationship between grade and IRR is not linear, but inverted and U-shaped. However, when considering the median, as the grade lowers the IRR increases. A scatterplot of borrowers’ interest rate (i) and internal rate of return (IRR) by grade provides a visual image of the data (Figure 2). The relationship between grade and borrowers’ interest rate is clearer than the relationship between grade and IRR.

**** Figure 2 ****

It can be recognized that the P2P lending market is not fully efficient. In an efficient market, there is no chance for lenders to obtain positive abnormal returns. However, this Table indicates that the use of simple strategies, such as funding credit card loans or wedding loans and avoiding small business or renewable energy loans, leads to increased profits. Simply stated, it is possible to "beat the market".

Table 4 shows the exploratory study of continuous independent variables. The first columns display the mean, median and standard deviation of failed and non-failed groups. The seventh and eighth columns display the results of both parametric and non-parametric means tests. As expected, loans that failed paid higher interest rates, 12.75%, compared to 11.14% for non-failed loans, and the difference is statistically significant. The average subgrade for failed loans is 24.82 (out of maximum 35), compared to 27.29 for non-failed loans. As expected, the average FICO score for failed loans (701.62) is lower than the average FICO score for non-failed loans (716.02). Average annual income for failed loans is $59,752, lower than non-failed, $68,694, and differences are statistically significant. As expected, both the credit history and borrower indebtedness are determinants of PD. Loan amounts for failed and non-failed loans are similar, and the differences are not statistically significant. Employment length does not appear to be a relevant variable for the PD.

**** Table 4 ****

Subsequent columns show the relationship between the borrower's interest rate and the independent variables. To this end, Pearson and Spearman correlation coefficients have been calculated and the results are coherent; the higher the grade and the FICO score is, the lower the borrower's interest rates, with coefficients nearing 1. For the remaining variables, correlations are statistically significant and have the expected sign but low magnitude. The only remarkable variables are revolving utilization which is over 0.5 and borrower indebtedness which is near 0.2.

The two final columns are the most relevant for this study because they show the relationship between IRR and the independent variables. It has been previously remarked that the relationship between grades and IRR was not linear, but complex. The Pearson correlation coefficient between IRR and borrowers' interest rate is nearly zero, while the Spearman correlation coefficient, obtained by performing a rank transformation, is 0.701, statistically significant and high. The remainder of the correlation coefficients is significant but very low. To summarize, the exploratory analysis has shown that the variables useful to predict loan default differ from the variables explaining loan profitability; this fact justifies the use of profit scoring.

3.4 Multivariate linear regression

Table 5 shows a multivariate linear regression using IRR as a dependent variable. The regression results provide a more in-depth analysis of the efficiency of the P2P loans market. The existence of factors determining IRR would indicate a lack of efficiency. Model 1 includes all the independent variables and, although the beta coefficients are statistically significant, its adjusted R^2 is very low, at 0.015. This is not surprising because we previously knew that the relationship between IRR and subgrade is inverted and U-shaped. Hence, multivariate linear regression does not appear to be adequate and several strategies could be implemented to improve the model's goodness of fit, such as adjusting a polynomic, adding squared variables or transforming the data. Because Spearman correlation coefficients were high, a variable rank transformation was performed. Conover and Iman [34] affirm that rank transformation provides a bridge between parametric and nonparametric statistics and is a method for presenting both the parametric and nonparametric methods in a unified manner. Model 2 and the subsequent models contain both rank transformations of the dependent variable, rIRR, and the interest rate (r-interest rate). Model 2 includes a single dependent variable, r-interest rate, with an adjusted R^2 of 0.491. Subsequent models incorporate loan purpose (Model 3), borrower characteristics (Model 4), credit history (Model 5) and indebtedness (Model 6). Gains in adjusted R^2 are minimal. Model 7 is the full model and obtains an adjusted R^2 of 0.498.

**** Table 5 ****

3.5 Decision trees results

Analysis of the regression results indicates that the P2P loans market is not fully efficient; a relationship exists between the variables, but this relationship is not linear. Developing profit scoring will be complex. Hence, the use of non-linear techniques such as non-linear regression, neural networks or decision trees is justified. Decision trees were selected because the goal was not only predictive capability but also interpretability of results, and decision trees produce a set of rules easy to assimilate. Decision trees allow for non-linear relations between predictive factors and IRR. For example, IRR may be positively related to annual income if the income is less than a certain amount, but negatively related if it is more than this amount, revealing a non-linear relationship between both variables.

Explanation requires only cross validation whereas prediction requires intertemporal validation, which implies testing predictive results over time [35]. The train sample includes all loans from January 1, 2008, through December 31, 2011. Out of 26,971 loans, 2,910 are failed loans. The test sample includes all loans allocated from January 1, 2012 through June 30, 2012. Of 13,930 loans, 1,890 are failed loans. Not every decision tree algorithm can deal with continuous variables, for this reason exhaustive CHAID was selected, an algorithm widely used in data mining studies [36, 37] and credit scoring [38, 39]. CHAID is a recursive partitioning method that for regression-type problems relies on the F-square test to determine the best next split at each step. At each step, CHAID selects the independent variable that possesses the strongest interaction with the dependent variable. Categories of each predictor are merged if they are not significantly different with respect to the dependent variable. CHAID was implemented through the use of IBM SPSS Decision Trees, version 19.

Table 6 displays part of CHAID analysis results. All the independent variables in Table 2 were utilized. The tree contains 72 terminal nodes, and Table 6 summarizes the train and test results of 10 of these nodes. Certain strategies for "beating the market" are revealed, for example, node 18: "lending to borrowers with annual income over $65,000 with only 1 or 2 inquiries in the last 6 months, and not for small business". On average, this strategy obtains a 6.06% IRR in the train and a 5.98% IRR in the test, outperforming 3.92%, the lenders' mean IRR. The median IRR is 11.74% in the train and 13.19% in the test, outperforming 11.22%, the lenders' median IRR. 17.17% of the borrowers in the test sample meet these criteria. Table 6 displays the branches for this node and reveals certain strategies that obtain positive abnormal returns.

**** Table 6 ****

3.6 Comparison with credit scoring' results

A final analysis was performed that compared the results of applying profit scoring to credit scoring. A logistic regression (LR) analysis was conducted to develop a credit score, being the dependent variable a dummy variable that notes "1" for fully paid loans and "0" for charged off loans. All of the independent variables in Table 2 were utilized to obtain the model. The train sample contains the same 26,971 loans, which includes 2,910 failed loans; and the test sample contains 13,930 loans, including 1,890 failed loans. LR provides a score ranging from 0 to 1 that may be interpreted as a loan's solvency indicator. Loans in the test sample were ranked according to their LR score. If a lender chooses the 100-best loans according to the LR credit score results, an average 5.98% IRR would be obtained. The identical study was performed to develop a profit score, by means of multivariate regression. For this analysis, the same lender choosing the 100-best loans according to the profit scoring would have obtained an average 11.92% IRR. When the CHAID is the technique used to select the 100-best loans, the lender would have obtained an average 8.57% IRR.

4. Discussion

4.1 Practical implications

If both lenders and P2P lending platforms employ accurate decisional systems, the P2P lending market will improve. In a perfect market there is a large number of lenders that are perfectly informed of the characteristics of the loans that they are funding. Profit scoring systems, such as the one proposed in the paper, can help lenders to decide their fund allocation. Lenders may select loans to maximize the profitability of their investments because the data are available, and the results outperform those obtained by credit scoring based on LR. For example, in the case analyzed, a simple rule obtained from a CHAID decision tree: "lending to borrowers with annual income over $65,000 with only 1 or 2 inquiries in the last 6 months, and not for small business" results in positive abnormal returns. Another perfect markets characteristic is that decision makers act in a rational way, however in P2P lending market herding behavior has been found [32], which can be reduced by means of profit scoring systems.

A perfect market achieves equilibrium, which means that the supply of loans offered by borrowers will equal the demand for loans, and the rate of interest will perfect reflect loan risk. Lending Club and other P2P lending platforms can use profit scoring systems to customize the algorithm they utilize to assign interest rates. This study demonstrates that certain clients with a high probability of default may be profitable. In fact, if loan allocation is determined by credit scoring systems aimed at solely predicting the PD, credit may be inaccessible to the riskiest borrowers, although they may be profitable [13]. It is more sensible to apply profit scoring systems that predict the IRR and, accordingly, set the borrowers' interest rate.

Finally, an increasingly perfect market benefits creditworthy borrowers. This is because the use of data mining techniques may drive the loans with expected negative returns out of the market, and creditworthy borrowers will obtain rational interest rates according to their risk levels, thus avoiding the risk premium required by lenders with fear of making an adverse selection.

4.2 Scholarly contributions

The first research question in the study deals with the design of profit scoring DSS for P2P lending. Unlike previous research regarding P2P lending based on credit scoring that attempts to predict the probability of default [6, 7], we develop a profit scoring DSS that attempts to predict the internal rate of return. The DSS is based on a multivariate regression model and on a CHAID decision tree. The proposed system outperforms credit scoring results based on a logistic regression. In the analyzed sample, the results indicate that a lender selecting the 100-best loans by applying credit scoring by means of logistic regression could obtain an average 5.98% internal rate of return. By contrast, a lender applying a profit scoring system using multivariate regression could obtain an average 11.92% internal rate of return. This is the first contribution of the paper. These findings are promising and open a new research avenue using other data mining techniques.

The second research question investigates the factors explaining profitability in P2P lending. Factors explaining the probability of default are well known [2, 3], while few studies analyze factors explaining profitability, due to the lack of data [4]. To the best of our knowledge, this is the first profit score application in the P2P lending context, using IRR as a dependent variable. The study finds that factors explaining the IRR are different from factors explaining the PD. For example, within the data analyzed, credit card loans possess a 9.29% PD and a 6.27% IRR. Car loans, with a lower PD (8.84%) are less profitable (4.54% IRR). The contrary also occurs; small business loans maintain a higher PD (20.44%), but their lender profitability is negative (-3.10% IRR). The study finds that the borrower's rate of interest, borrower's indebtedness, and loan purpose are all factors explaining the IRR, although the relationship is not linear. This is the second contribution of the paper.

The third research question tests the efficiency of the P2P lending market. In an efficient market, there is no chance for lenders to obtain positive abnormal returns by selecting borrowers, because the borrowers' rate of interest fully reflects all available information in the credit market [20]. However, our empirical study finds that the use of simple rules, obtained from a CHAID decision tree, leads to increased profits. In other words, the P2P lending market is not currently a fully efficient market. This means that data mining techniques are able to identify the most profitable loans, or in financial jargon, "beat the market". This is the third contribution of the paper.

The use of DSS, such as the one proposed in the paper, can improve the P2P lending market, one of whose aims is to smoothly resemble a perfect market. In a perfect market the supply of loans offered by borrowers will equal the demand for loans and the rate of interest will exactly reflect the risk of the loan. This requires not only to have high-quality information about the applicants, but also that this information be analyzed with appropriate data mining tools. In other words, the use of a DSS may enable the lenders to take more rational decisions, avoiding irrational herding behavior.

4.3 Limitations of the study

This study analyzes data from a single electronic platform, Lending Club. Factors determining the IRR have been identified, but these results cannot be extended to other P2P lending platforms; the rules obtained only apply to the analyzed case. For example, this study finds that, in the case analyzed, small business loans are not profitable, but these loans could be profitable if the borrower's interest rate is high enough to compensate for its delinquency, as could happen in any other electronic platform or even in Lending Club if they adjust the method of setting interest rates. In other words, following trading disclaimers "past performance is not indicative of future results".

4.4 Future directions

Other data mining techniques may be applied to develop profit score systems, such as support vector regression, neural networks or regression-trees. It would be enlightening to compare the assessment of several techniques and identify those that are better performing. Profit scoring may be applied in other contexts, such as microcredits offered by microfinance institutions. Another future opportunity for study may be the efficiency of P2P lending markets and whether profit score systems might improve that efficiency.

5. Conclusions

This paper proposes a profit scoring DSS for P2P lending. The analysis goes beyond credit scoring DSS since it is not limited to predict the probability of default, but focuses on lender profitability. Credit scoring systems require a dichotomous variable as a dependent variable, assigning “0” to failed loans and “1” to successful loans. Profit scoring systems utilize a continuous variable measuring profitability as a dependent variable. This paper uses the internal rate of return (IRR), the effective interest rate that the lender receives. IRR is different from the interest rate the borrower pays, due to delinquent loans and recovery fees. A profit scoring needs to gather data on the payments made by each borrower, including the recovery of delinquent loans and many types of fees. The data from the empirical study were extracted from Lending Club, the largest U.S. P2P platform.

Our study shows that clients with a high probability of default may also be profitable. Factors explaining the profitability are different from factors explaining default. An exploratory analysis and a multivariate regression reveal a non-linear relationship between the IRR and its determinants. The primary factor explaining the IRR is the subgrade, but the relationship is inverted and U-shaped. This suggests that non-linear data mining techniques may be very useful to develop profit scoring systems. CHAID, which is a decision tree capable of analyzing continuous variables, discovering non-linear relationships and generating rules easy to interpret, was utilized for this study. Lenders incorporating such rules may “beat the market” and outperform the average IRR in the Lending Club. However, the rules cannot be generalized to other contexts, periods or electronic platforms. In other words, “past performance does not guarantee future results”.

The Lending Club is competent when determining the probability of default, where the riskiest loans receive low grades and pay high interest rates. However, certain inconsistencies have arisen; credit scoring models are not perfect, and the method utilized by Lending Club is still being fine-tuned. If the P2P lending market were fully efficient, the price of the loans, that is, the borrower’s interest rates, would reflect all of the available information. The results indicate that P2P lending is not completely efficient when setting the interest rates, but this lack of efficiency is characteristic of many financial markets such as the stock exchange market. However, transparency improves market efficiency and Lending Club makes a remarkable effort towards transparency; it discloses all borrower data, including characteristics, credit history and loan payments. Because data are freely available, individual lenders and researchers may develop new profit scoring DSS by utilizing different data mining techniques. The use of profit scoring DSS, such as the one proposed in the paper, can improve the P2P lending market, one of whose aims is to smoothly resemble a perfect market. We encourage moving from the sole use of credit score systems and developing profit score systems.

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Study	Description	Technique	Profitability approach	Performance
Andreeva et al. (2007) [29]	A profit-based scoring system is developed using data from a store card, used to buy white durable goods in Germany	Survival analysis and logistic regression	The present value of net revenue from a revolving credit account is calculated	The model which estimates the revenue performs better than the logistic regression, but the difference is small
Finlay (2008) [28]	Continuous models of customer worth are compared to binary models of customer repayment behavior. Data were supplied by a provider of retail credit	Linear regression and logistic regression	A measure of the worth of each customer, including estimates of payments that contribute to profits and estimates of costs that reduce profits	Models of customer worth significantly outperform standard classification methodologies when ranking accounts based on their financial worth to lenders
Finlay (2010) [12]	A comparison of predictive models of continuous financial behavior with binary models of customer default. Data originate from a provider of retail credit	Linear regression, genetic algorithms, neural networks and logistic regression	The profit from each credit account is calculated as net revenue minus bad debt	Scoring functions developed to specifically optimize profit contribution outperform credit scoring approaches
Stewart (2011) [13]	A profit-based scoring system for credit cards. Data set supplied by a private bank consisting of accounts approved for a prime credit card	Optimal binning for scoring modeling	The profit-based scoring system uses spending as a proxy for revenue and charge-off as a proxy for costs	The results suggest a profit-based scoring system segmented by risk and predicting spend improves upon a risk-only strategy
Barrios et al. (2013) [14]	Absolute and relative scorecards for assessing profits in consumer revolving credit. Data originate from a Colombian lending institution	Linear regression and logistic regression	The relative profit measure is the customer lifetime value divided by the outstanding debt	Time-to-profit scorecards outperformed traditional scorecards in regards to portfolio returns
Verbraken et al. (2014) [15]	A profit-based classification performance measure for credit scoring. Two datasets composed of loans for micro-entrepreneurs granted by a government organization	Logistic regression and artificial neural networks	The performance measure is based on the expected maximum profit measure	The use of the expected maximum profit measure for model selection leads to more profitable credit scoring models
So et al. (2014) [16]	A profitability model for potential credit card applicants including the transactor/revolver score leads. Credit card data originate from a Hong Kong financial institution	Logistic regression	The profitability model includes the chance that the applicants will take the credit card offered, depending on the interest rate charged and on the riskiness of the applicants	This model results in more accurate profitability estimates than models that ignore the transactor/revolver split
Lessmann et al. (2015) [3]	A comparison of algorithms for both credit and profit scoring. Eight real-word credit scoring data sets	41 different classification algorithms	The scorecard profitability is estimated by examining classification errors costs	The most accurate classifier does not necessarily give the most profitable scorecard

Table 1. Literature review.

Variable	Definition
Dependent variable	
Internal rate of return (IRR)	Internal rate of return calculated as the effective interest rate received by the lender
Borrower Assessment	
Grade	Lending Club categorizes borrowers into seven different loan grades from A down to G, A-grade being the safest
Subgrade	There are 35 loan subgrades in total for borrowers from A1 down to G5, A1-subgrade being the safest
FICO	A measure of consumer credit risk, based on credit reports that range from 300 to 850. FICO® is a registered trademarks of Fair Isaac Corporation
Borrowers' interest rate (i)	Interest rate on the loan payed by the borrower
Loan Characteristics	
Loan purpose	14 loan purposes: wedding, credit card, car loan, major purchase, home improvement, debt consolidation, house, vacation, medical, moving, renewable energy, educational, small business, and other
Loan amount	The listed amount of the loan applied for by the borrower
Borrower Characteristics	
Annual income	The annual income provided by the borrower during registration
Housing situation	Own, rent, mortgage and other
Employment length	The length of time (years) that workers have been with their current employer
Credit History	
Credit history length	Number of days of credit history considering the date when the borrower's earliest reported credit line was opened
Delinquency 2 years	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years
Inquiries last 6 months	The number of inquiries by creditors during the past 6 months
Public records	Number of derogatory public records
Revolving utilization	Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
Open accounts	The number of open credit lines in the borrower's credit file
Months since last delinquency	The number of months since the borrower's last delinquency
Borrower Indebtedness	
Loan amount to annual income	Loan amount to annual income
Annual instalment to income	The annual payment owed by the borrower divided by the annual income provided by the borrower during registration
Debt to income	Borrower's debt to income ratio. Monthly payments on the total debt obligations, excluding mortgage, divided by self-reported monthly income.

Table 2. Variables used in the study.

	Number of loans (%)	Probability of default (PD)			Borrowers' interest rate (i)				Lenders' profitability (IRR)			
		Failed (%)	Chi^2, sig	Phi	Mean	Median	St dev	T-test	Mean	Median	St dev	T-test
Grade												
A	13,222 (32.33%)	831 (6.28%)	560.39***	-0.117***	7.42%	7.51%	0.01	-335.76***	3.79%	7.88%	0.17	-0.781***
B	13,742 (33.60%)	1,586 (11.54%)	0.75	-0.004	11.33%	11.14%	0.01	0.02	4.33%	11.71%	0.25	2.37***
C	8,169 (19.97%)	1,271 (15.56%)	144.04***	0.059***	13.94%	13.98%	0.01	143.19***	3.63%	14.60%	0.30	-0.99***
D	4,436 (10.85%)	819 (18.46%)	217.37***	0.073***	16.15%	15.99%	0.01	194.94***	3.91%	16.84%	0.33	-0.02***
E	1,046 (2.56%)	216 (20.65%)	82.35***	0.045***	17.78%	17.19%	0.02	110.45***	3.03%	18.16%	0.36	-0.81***
F	224 (0.55%)	56 (25.00%)	38.26***	0.031***	19.27%	18.99%	0.02	66.04***	2.15%	20.14%	0.38	-0.69***
G	62 (0.15%)	21 (33.87%)	29.37***	0.027***	21.03%	20.32%	0.02	40.78***	-2.80%	21.91%	0.45	-1.18***
Loan purpose												
Major purchase	2,031 (4.97%)	163 (8.03%)	28.40***	-0.026***	10.17%	9.88%	0.03	-15.71***	5.06%	9.33%	0.22	2.38***
Wedding	943 (2.31%)	79 (8.38%)	10.51***	-0.016***	11.26%	11.34%	0.03	-0.69	5.27%	11.33%	0.25	1.7***
Car loan	1,210 (2.96%)	107 (8.84%)	10.07***	-0.016***	9.76%	8.90%	0.03	-16.22***	4.54%	8.35%	0.22	1.01***
Credit card	6,698 (16.38%)	622 (9.29%)	46.39***	-0.034***	11.38%	11.49%	0.03	1.33	6.27%	11.33%	0.21	9.46**
Home improvement	2,743 (6.71%)	261 (9.52%)	14.00***	-0.018***	10.44%	10.25%	0.03	-14.21***	4.52%	9.76%	0.23	1.41***
Debt consolidation	19,560 (47.82%)	2,394 (12.24%)	9.18***	0.015***	11.68%	11.83%	0.03	19.85***	4.06%	11.40%	0.26	1.08***
House	364 (0.89%)	48 (13.19%)	0.75	0.004	10.87%	10.39%	0.03	-2.6***	1.41%	10.23%	0.29	-1.68***
Vacation	401 (0.98%)	54 (13.47%)	1.17	0.005	10.75%	10.59%	0.03	-3.45***	2.46%	10.36%	0.27	-1.15***
Other	3,720 (9.10%)	504 (13.55%)	12.98***	0.018***	11.23%	11.27%	0.03	-2.08**	1.94%	10.95%	0.28	-4.49***
Medical	684 (1.67%)	97 (14.18%)	4.02**	0.010**	10.92%	10.75%	0.03	-3.16***	0.96%	10.18%	0.29	-2.66***
Moving	581 (1.42%)	83 (14.29%)	3.70*	0.010*	11.10%	10.99%	0.03	-1.65	1.81%	10.92%	0.28	-1.81***
Educational	278 (0.68%)	44 (15.83%)	4.52**	0.011**	11.59%	11.89%	0.02	1.77*	1.56%	11.82%	0.29	-1.36***
Renewable energy	88 (0.22%)	17 (19.32%)	4.90**	0.011**	10.63%	10.69%	0.03	-1.94*	-3.20%	9.85%	0.34	-1.96***
Small business	1,600 (3.91%)	327 (20.44%)	121.73***	0.055***	11.85%	11.71%	0.04	5.69***	-3.10%	10.46%	0.35	-8.35***
Housing situation												
Mortgage	16,755 (40.96%)	1,723 (10.28%)	57.78***	-0.038***	10.86%	10.74%	0.03	-23.11***	4.64%	10.42%	0.23	4.92***
Own	3,133 (7.66%)	384 (12.26%)	0.89	0.005	11.26%	11.26%	0.03	-1.27	3.50%	11.02%	0.26	-0.95***
Rent	20,920 (51.15%)	2,677 (12.80%)	46.51***	0.034***	11.72%	11.86%	0.03	23.44***	3.42%	11.51%	0.27	-4.07***
Other	92 (0.22%)	16 (17.39%)	2.85*	0.008*	11.93%	11.83%	0.03	2.15**	-0.62%	11.78%	0.33	-1.34***

Table 3. Exploratory study on discrete variables. Number of loans analyzed: 40,901. Failed: 4,800 (11.74%). Non-failed: 36,101 (88.26%). Borrowers' mean interest rate is 11.33% and median is 11.36%. Lenders' mean IRR is 3.92% and median is 11.22%.

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

	Failed (N=4,800)			Non failed (N=36,101)			Univariate test		Borrowers' interest rate (i)		Lenders' profitability (IRR)	
	Mean	**Median**	**St dev**	**Mean**	**Median**	**St dev**	**T-test**	**Median test**	**Pearson**	**Spearman**	**Pearson**	**Spearman**
Borrower Assessment												
Borrowers' interest rate (i)	12.75%	12.98%	0.03	11.14%	10.99%	0.03	-31.26***	640.01***	1	1	-0.002	0.701***
Subgrade (From A1=1 to G5=35)	24.82	26	5.73	27.29	28	5.40	28.2***	585.83***	-0.947***	-0.969***	0.006	-0.682***
FICO	701.62	697	30.29	716.02	712	35.68	30.26***	504.30***	-0.797***	-0.837***	0.005	-0.588***
Loan Characteristics												
Loan Amount	10,343	9,000	6,729	10,317	9,000	6,689	-0.25	0.04	0.170***	0.132***	0.021***	0.091***
Borrower Characteristics												
Annual Income	59,752	50,004	41,542	68,694	59,000	60,121	13.19***	170.02***	0.021***	0.006***	0.049***	0.047***
Employment Length	4.99	4	3.56	4.98	4	3.55	-0.35	0.24	-0.024***	-0.029***	0.005	-0.027***
Credit History												
Credit History Length	4,689	4,291	2,387	4,931	4,475	2,413	6.58***	35.11***	-0.149***	-0.167***	0.012**	-0.115***
Delinquency 2 Years	0.17	0	0.51	0.14	0	0.49	-3.62***	21.25***	0.169***	0.180***	0.006	0.132***
Inquiries Last 6 Months	1.01	1	1.13	0.79	0	1.01	-12.33***	128.74***	0.136***	0.172***	-0.055***	0.096***
Public Records	0.07	0	0.26	0.04	0	0.21	-6.32***	57.70***	0.085***	0.088***	-0.011**	0.047***
Revolving Utilization	0.57	0.61	0.27	0.50	0.52	0.28	-17.97***	237.31***	0.502***	0.508***	-0.006	0.355***
Open Accounts	9.39	9	4.53	9.45	9	4.35	0.98	1.50	0.030***	-0.013***	0.013***	-0.008*
Months Since Last Delinquency	35.59	33	21.88	36.86	35	21.56	2.3**	1.84	-0.097***	-0.090***	0.015*	-0.061***
Borrower Indebtedness												
Loan Amount to Annual Income	0.20	0.17	0.12	0.17	0.15	0.11	-13.19***	103.70***	0.125***	0.130***	-0.051***	0.056***
Annual Instalment to Income	0.08	0.07	0.05	0.07	0.06	0.04	-15.16***	136.46***	0.204***	0.198***	-0.051***	0.105***
Debt to Income	14.41	14.71	6.75	13.54	13.54	6.74	-8.46***	58.10***	0.104***	0.110***	-0.024***	0.064***

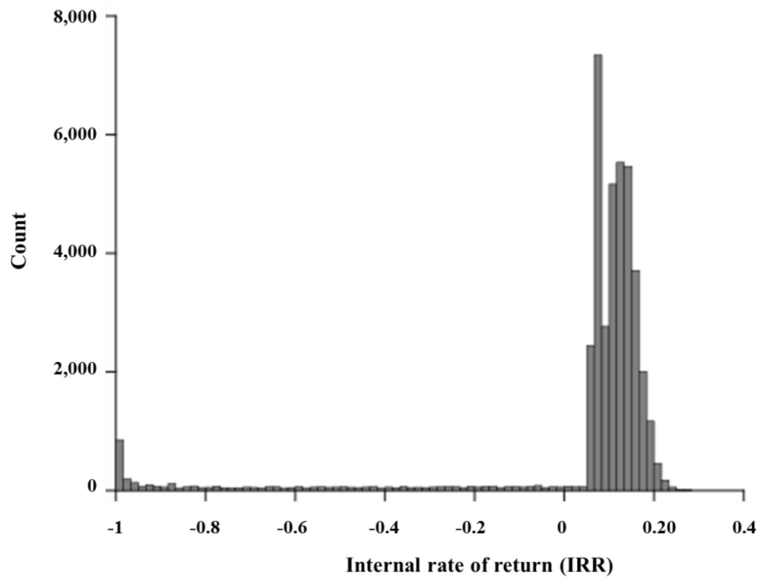
Table 4. Exploratory study on continuous variables. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

	Model 1 IRR	Model 2 rIRR	Model 3 rIRR	Model 4 rIRR	Model 5 rIRR	Model 6 rIRR	Model 7 rIRR
Borrower Assessment							
Interest rate	0.100***						
FICO	0.043***						0.008
r-interest rate		0.701***	0.702***	0.700***	0.709***	0.760***	0.785***
Purpose							
Major purchase	-0.001		0.007**				0.002
Wedding	0.003		0.011***				0.007**
Car loan	-0.003		0.001				-0.002
Credit card	0.032***		0.023***				0.022***
Home Improvement	-0.010*		0.002				-0.005
House	-0.009*		-0.006				-0.005
Vacation	-0.011**		-0.002				-0.005
Other	-0.033***		-0.010*				-0.017***
Medical	-0.021***		-0.009**				-0.013***
Moving	-0.015***		-0.003				-0.007*
Educational	-0.009*		-0.003				-0.005
Renewable energy	-0.015***		-0.005				-0.006*
Small Business	-0.060***		-0.004***				-0.035***
Borrower Characteristics							
Annual Income	0.030***			0.027***			0.017***
Housing Situation: Mortgage	0.018***			-0.001			0.004
Housing Situation: Own	0.003			-0.004			-0.001
Housing Situation: Other	-0.007			-0.005			-0.004
Credit history							
Credit history length	-0.003				0.003		-0.003
Delinquency 2 Years	0.000				0.006		0.001
Inquiries Last 6 Months	-0.065***				-0.031***		-0.034***
Public Records	-0.011**				-0.014***		-0.016***
Revolving Utilization	-0.029***				-0.007		-0.018***
Indebtedness							
Loan Amount to Annual Income	0.373***					0.649***	0.687***
Annual Instalment to Income	-0.440***					-0.701***	-0.742***
N. obs.	40,901	40,901	40,901	40,901	40,901	40,901	40,901
Adjusted R^2	0.015	0.491	0.493	0.491	0.492	0.494	0.498

Table 5: Regression analysis for the determinants of IRR (internal rate of return). *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Sample	Node	Rule	Mean IRR	Median IRR	N	Percent
Training	18	Annual income > 65,000; Not small business; 0<Inquiries last 6 months ≤ 2	6.06%	11.74%	4,374	16.22%
	115	Annual income > 65,000; Not small business; 0<Inquiries last 6 months ≤ 2; Grade D; Interest rate < 0.13	9.58%	16.49%	524	1.94%
	107	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A; Public records =0; credit history length > 4,413	9.12%	12.56%	1,830	6.79%
	105	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A; Public records = 0; credit history length ≤ 3,956	8.88%	12.67%	770	2.85%
	112	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; 0.12 < Loan amount to annual income ≤ 0.12	7.26%	11.26%	1,101	4.08%
	108	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A nor E; Public records > 0	4.99%	12.27%	176	0.65%
	111	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; 0.05 < Loan amount to annual income ≤ 0.12	5.37%	10.59%	1,501	5.57%
	110	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; Loan amount to annual income ≤ 0.05	7.27%	11.11%	644	2.38%
	113	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; 0.12 < Loan amount to annual income >0. 2	2.30%	12.03%	529	1.96%
	106	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A; Public records = 0; 3,956< credit history length ≤ 4,413	3.69%	12.26%	290	1.08%
Test	18	Annual income > 65,000; Not small business; 0<Inquiries last 6 months ≤ 2	5.98%	13.19%	2,392	17.17%
	115	Annual income > 65,000; Not small business; 0<Inquiries last 6 months ≤ 2; Grade D; Interest rate < 0.13	8.42%	18.87%	295	2.12%
	107	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A; Public records =0; credit history length > 4,413	6.98%	13.50%	1,044	7.49%
	105	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A; Public records = 0; credit history length ≤ 3,956	8.42%	13.19%	460	3.30%
	112	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; 0.12 < Loan amount to annual income ≤ 0.12	5.34%	12.87%	663	4.76%
	108	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A nor E; Public records > 0	4.71%	13.54%	48	0.34%
	111	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; 0.05 < Loan amount to annual income ≤ 0.12	5.11%	11.34%	724	5.20%
	110	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; Loan amount to annual income ≤ 0.05	8.39%	11.48%	226	1.62%
	113	Annual income > 65,000; Not small business; 0 <Inquiries last 6 months ≤2; Not Grade F nor D; 0.12 < Loan amount to annual income >0. 2	5.37%	12.83%	476	3.42%
	106	Annual income > 65,000; Not small business; Inquiries last 6 months = 0; Not Grade A; Public records = 0; 3,956< credit history length ≤ 4,413	4.72%	12.93%	187	1.34%

Table 6. Decision rules for the prediction of the IRR from the CHAID algorithm. Growing method: exhaustive CHAID. IRR: lenders' internal rate of return. N = 40,901 loans. Train sample contains 26,971 loans from 2008 to 2011, including 2,910 failed loans. Test sample contains 13,930 loans from January to June 2012, including 1,890 failed loans.



N	40,901
Mean	0.0392
St dev.	0.2591
Skewness	-3.115
Kurtosis	8.696
Minimum	-1
Percentile 10	-0.0892
Percentile 20	0.0701
Percentile 30	0.0820
Percentile 40	0.0939
Median	0.1122
Percentile 60	0.1241
Percentile 70	0.1362
Percentile 80	0.1483
Percentile 90	0.1651
Maximum	0.2798

Figure 1. Loans' IRR histogram.

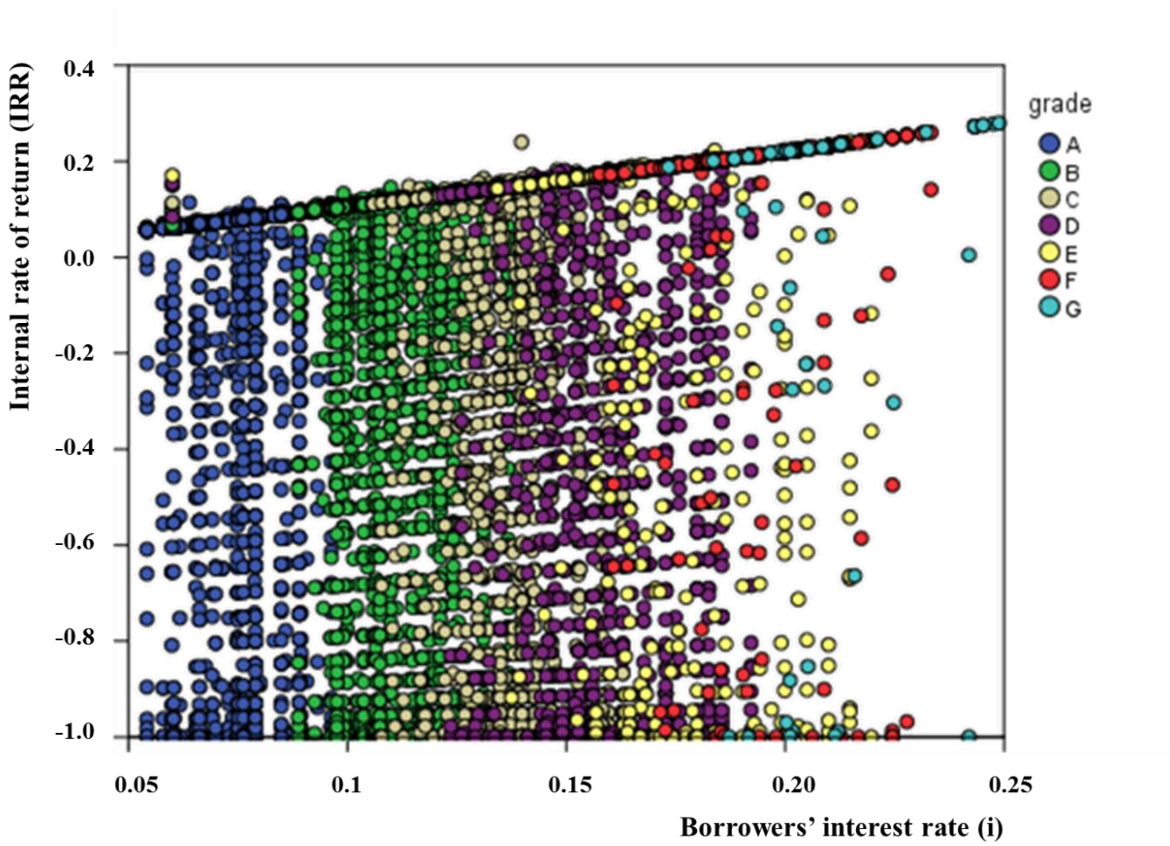


Figure 2. Scatterplot of borrowers' interest rate (i) vs internal rate of return (IRR) by grade.