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Profitability score metrics in Peer-to-Peer debt-based crowdfunding: evidence from the United States

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Abstract

Peer-to-Peer (P2P) lending markets offer risk diversification opportunities for the crowd of lenders, usually informal ones. Crowdlenders face information asymmetries in P2P platforms, usually mitigated through credit scoring models. We merge credit scoring and profitability literature to understand how crowdlenders should use debt-crowdfunding campaigns' hard information to maximize investment return based on risk. Based on 62,081 loans granted on the Lending Club, a US-leading P2P debt crowdfunding platform, between 2010 and 2018, we find that crowdlenders selecting low and medium credit risk campaigns should opt for: smaller loans whose borrowers have higher incomes, longer number of years employed, lower indebtedness, and overall better credit history, to maximize their returns per unit of risk. These results contribute to the literature on the risk-return nexus that has received limited attention in Peer-to-Peer lending markets.

Keywords: Credit Risk, Credit Score, Profitability, Debt Crowdfunding, Lending Club

Métricas de classificação da lucratividade no crowdfunding Peer-to-Peer baseado em dívida: evidências dos Estados Unidos da América

Resumo

Os mercados de empréstimos Peer to Peer (P2P) oferecem oportunidades de diversificação de risco para os credores (*crowdlenders)*, normalmente informais. Os *crowdlenders* enfrentam assimetrias de informação nas plataformas P2P, geralmente mitigadas através de modelos de classificação de risco de crédito. Neste estudo, mesclamos a literatura sobre a classificação de risco de crédito e a literatura sobre lucratividade para entender de que forma os *crowdlenders* devem utilizar a informação *hard* da campanha de empréstimo para assim maximizarem o seu retorno, de acordo com a sua propensão ao risco. Com base em 62,081 campanhas de empréstimo, recolhidas no período de 2010-2018 através da plataforma *Lending Club*, verificamos que os *crowdlenders* que selecionam campanhas de baixo e médio risco de crédito devem optar por: empréstimos de menores montantes, cujos mutuários possuem rendimentos mais elevados, maior estabilidade no emprego, menor endividamento, e melhor histórico de crédito em geral, para aumentar a sua lucratividade excedente por unidade de risco. Estes resultados contribuem para a literatura sobre o binómio *risco-retorno* que tem recebido uma atenção limitada nos mercados de empréstimos entre pares.

Palavras-chave: Risco de crédito, Score de crédito, Lucratividade, Crowdfunding, Lending Club

1. Introduction

With the advent of Web2 (Moysidou & Hausberg, 2020; Stalnaker, 2008) and Fintech, Peer-to-peer (P2P) lending markets have undergone a rapid development (Ge et al., 2017; Zhou et al., 2018). One of the reasons for this fast growth is the critical role of those markets in financial disintermediation (Fiaschi et al., 2014; Fitzpatrick & Mues, 2021). Through a collaborative economy (Belk, 2014), P2P lending is an alternative funding channel to traditional financial markets (de Roure et al., 2021; Jagtiani & Lemieux, 2018; Tang et al., 2020; Tao et al., 2017; Yoon et al., 2019), namely to financially excluded people (Yum et al., 2012). P2P lending is a type of crowdfunding where funds are offered to borrowers to support their projects through a loan where lenders expect a return on their invested capital (Mollick, 2014). These individuals are part of a large crowd of small non-institutional lenders (Allison et al., 2015; Dorfleitner et al., 2021; Mild et al., 2015). For non-institutional lenders, P2P lending crowdfunding offers the opportunity to support borrower's initiatives (Schwienbacher & Larralde, 2010) and to diversify their investments (Bholat & Atz, 2016; Cumming & Hornuf, 2018) therefore reducing their portfolio risk. For the economy, P2P lending crowdfunding promotes self-employment, entrepreneurship, growth, and socio-economic development (Kgoroeadira et al., 2019; M. Lin, Prabhala et al., 2013; Morduch, 1999).

The first P2P lending platform--Zopa -- was founded in March 2005 (Wang & Tong, 2020). Besides debt-based crowdfunding, other forms of online crowdfunding have emerged, such as donation-based (Zhang et al., 2020), reward-based (Agrawal et al., 2015; Colombo et al., 2014; Mollick & Nanda, 2016), prosocial-based loan campaigns (Allison et al., 2015), and equity-based crowdfunding (Ahlers et al., 2015; Hornuf & Schwienbacher, 2018; Vismara, 2016). Crowdfunding platforms operate in two alternative business models: *Keep-It-All* (KIP), where the amount raised is always kept by borrowers, and, thus, meeting the fundraising goal is not necessary to receive funding; and, *All-Or-Nothing* (AON), where meeting the fundraising goal is required to collect funding to finance the crowdfunding campaign (Miglo & Miglo, 2019).

In P2P lending markets, the borrower-lender relationship is intermediated by the crowdfunding platform that acts as a third party that brokers capital flows between the crowd of lenders and borrowers (Havrylchyk & Verdier, 2018). In exchange for this intermediation role, they charge a fee or interest rate, transaction costs, and any additional charges (Berger & Gleisner, 2009; Serrano-Cinca et al., 2015; Wallmeroth et al., 2018). In these P2P crowdfunding platforms, crowdlenders face information asymmetry issues (Emekter et al., 2015) arising from adverse selection (Akerlof, 1970) and moral hazard problems (Stiglitz & Weiss, 1981). The asymmetric-information problem has several causes, such as lower means of debt recovery (Emekter et al., 2015), lack of knowledge about borrower's credit history, or absence of relationship lending (Garmaise & Natividad, 2010; J. Huang et al., 2021). A possible solution to mitigate asymmetric information is the attribution of a credit score by the P2P crowdfunding platforms to each loan campaign evaluating credit quality according to their ability to repay the debt (Arya et al., 2013; Bastani et al., 2018; Einav et al., 2013). In P2P lending crowdfunding, the potential crowdlenders have access to incomplete information regarding the project quality and the borrower's reputation. To reduce this problem, P2P platforms rely on available information they collect on borrowers and their campaigns, which might include the loan purpose, loan amount, duration of employment, borrower's annual earnings, borrower's history, and borrower's debt (Florez & Ramon, 2014; Lessmann et al., 2015).

Following traditional banking sector practices, credit scoring is based on a probabilistic model that differentiates likely default from non-default loans (Zhou et al., 2018). Credit score focuses only on credit risk, which does not make it informative enough for crowdlenders whose primary goal is to maximize the results of the invested capital (Bastani et al., 2018; Eisenbeis, 1977). So, despite its recognized advantages, a new stream of research has pointed out several critics and limitations to the credit score as a decision tool for crowdlenders (e.g., Bastani et al., 2018; Fitzpatrick & Mues, 2021; Guo et al., 2016; Lyócsa et al., 2022; Serrano-Cinca & Gutiérrez-Nieto, 2016). First, credit scoring does not provide an analysis of potential profitable-loan interest rates for crowdlenders (Serrano-Cinca et al., 2015). Second, it mainly focuses on credit risk – the probability of default (Zhou et al., 2018), and it fails to account for the Loss Given Default (Calabrese & Zanin, 2022; Zhou et al., 2018). Third, this metric assumes that equal errors have the same costs– the so-called *equal costs problem*–but overvalued loans have much higher costs than undervalued loans (Liu et al., 2018).

To fill this void, new metrics have been analyzed to offer crowdlenders better results on invested capital. To classify the market value of each campaign, Lessmann et al. (2015) recommend looking at the ratio of expected return, a metric less focused on the borrower's credit history. A body of literature on debt-based crowdfunding has been following this reasoning (e.g., Bastani et al., 2018; Fitzpatrick & Mues, 2021; Guo et al., 2016; Serrano-Cinca & Gutiérrez-Nieto, 2016) by looking to measures of profitability (e.g., Internal Rate of Return – IRR; Serrano-Cinca & Gutiérrez-Nieto, 2016). Arguably, profitability measures provide a more holistic view of the campaign's value to crowdlenders, considering regular and default interest, forced recoveries, and upfront payments, in addition to losses on default, not focusing only on the probability of default as is the case of credit scoring models.

Although the advances in this field of research, we argue that profitability analyzes should be driven by the crowdlenders' risk profile. Otherwise, a metric based on profitability that ignores the binomial risk-return might favor riskier loans, usually associated with higher interest rates (Hand & Henley, 1997). This study aims to fill this gap by answering the following research question: *What characteristics should crowdlenders focus on to increase their profitability per unit of risk in P2P lending crowdfunding?* To this end, we merge credit scoring and profitability metrics to understand how borrower information and campaigns can maximize return on investment based on profitability and credit risk. Thus, we offer potential guidance to crowdlenders to improve their decision-making according to their risk.

For this purpose, we use a sample of 62,081 loan campaigns granted between 2010-2018 on Lending Club, one of the largest crowdlending platforms in the United States (US). Based on probabilistic models and linear regressions, our results suggest that crowdlenders of low and medium credit risk campaigns should opt for: smaller loans whose borrowers have higher incomes, longer number of years, lower indebtedness, and overall better credit history, results that seem to match the empirical background present in the previous literature.

This study offers three main contributions to the P2P lending crowdfunding market, practitioners, and to debt-based crowdfunding literature. First, we contribute to studying information asymmetry problems and the success of crowdfunding repayment by merging credit scoring and profitability literature. Regarding crowdlenders, we offer investment guidelines to support their financial decision-making to increase profitability per unit of risk in their crowdfunding investments. Finally, our results support that, in general, a higher return is not achieved through taking greater risks since the results suggest that it is through risk reduction (i.e., choosing higher-income borrowers, greater stability in employment, lower indebtedness and better credit history and taking smaller loans) that leads crowdlenders to achieve better effective results in the profitability of their crowdfunding investments. Our finding is in line with the results of the literature that investigates the probability of default in debt-based crowdfunding, namely with Berkovich (2011) and Emekter et al. (2015). These authors provide evidence that the sustainable growth of the P2P debt-based crowdfunding market would involve attracting a more significant number of lower risk customers.

This study is organized as follows. Section 2 reviews the literature on information asymmetries and risk-return measurement in P2P lending crowdfunding. Section 3 describes the data, variables, and method. Section 4 reports the results and answers to our research question. Section 5 discusses the main results and Section 6 concludes.

2. Literature review

2.1. Information Asymmetries

Information asymmetry problems are complex and affect both the traditional credit markets (Myers & Majluf, 1984) and the P2P lending crowdfunding market (Lin et al., 2017). In the P2P crowdfunding market crowdlenders have limited and imperfect information about borrowers, their projects, and lending crowdfunding campaigns (Emekter et al., 2015; Wei et al., 2020). Usually, the information provided by the borrower regarding the project is not subject to complex screening processes (Emekter et al., 2015; Serrano-Cinca et al., 2015) since non-institutional crowdlenders tend to be informal investors and not specialists in financial or risk analysis (Guo et al., 2016; Klafft, 2008), lacking the ability to perform due diligence. Hence, borrowers may purposely withhold harmful information (Liu et al., 2018), leading crowdlenders to receive incomplete information. This is the so-called *adverse selection problem* (Stiglitz & Weiss, 1981). That is, crowdlenders may choose a crowdfunding campaign from a bad borrower over a campaign from a good one without better observable information. In traditional markets, information asymmetries can also lead to *moral hazard problems*, namely those arising from ex post frictions, such as asset substitution events or risk-shifting behaviors (Akerlof, 1970; Bebczuk, 2003). The limited monitoring abilities of crowdlenders increase their exposure to those risks in P2P lending crowdfunding. Because P2P crowdfunding exacerbates information asymmetry problems

(Ahlers et al., 2015; M. Lin, Prabhala, et al., 2013; X. Lin et al., 2017; Prystav, 2016; X. Wei et al., 2020), one can argue that this market is even more exposed than traditional ones to the "Lemons" dilemma[1].

P2P lending platforms lack the financial and risk-analysis tools that traditional financial institutions have to mitigate asymmetric-information problems (Serrano-Cinca & Gutiérrez-Nieto, 2016), such as guarantees protection against loan default and screening or monitoring tools (Emekter et al., 2015; Jagtiani & Lemieux, 2018; Mild et al., 2015; Yoon et al., 2019). Implementing such mechanisms in the P2P lending crowdfunding market would increase transaction costs in loan campaigns and, therefore, to a loss of competitive advantages in this market (Mild et al., 2015; Serrano-Cinca et al., 2015; Yoon et al., 2019). Additionally, in P2P crowdfunding platforms, borrowers usually apply for online lending only once (Feller et al., 2014; Serrano-Cinca et al., 2015). This prevents a strong lending relationship that would produce valuable (soft) information regarding the borrowers' credibility and loan quality. In such a context, the intermediation of P2P platforms plays an essential role in crowdfunding market regulation (Hui Huang, 2016; Moysidou & Hausberg, 2020; Pokorná & Sponer, 2016; Segal, 2015) as well as in reducing information asymmetry problem (Emekter et al., 2015; Gao et al., 2021; Iyer et al., 2016).

P2P platforms offer a possible solution to mitigate the problem of asymmetric information (Jagtiani & Lemieux, 2018; Serrano-Cinca & Gutiérrez-Nieto, 2016) through credit scoring built from big data analysis (Wei & Lin, 2017), which in turn generates trust among crowdlenders, and reinforce trust on the P2P platforms and the campaigns made public in those platforms. However, the credit risk analysis provided by P2P platforms is not absent of inaccuracies since crowdfunding platforms' assessments focus primarily on maximizing their profit (Ortega & Bell, 2008) in the case of for-profit crowdfunding organizations. To mitigate asymmetry information and inefficiencies in the capital allocation process, non-institutional crowdlenders might use hard (Emekter et al., 2015; Jin & Zhu, 2015; Serrano-Cinca et al., 2015; Wei & Zhou, 2018) and soft information (Courtney et al., 2017; Dorfleitner et al., 2016; Freedman & Jin, 2017; Herzenstein et al., 2011; Kgoroeadira et al., 2019; M. Lin, Prabhala, et al., 2013; Pope & Sydnor, 2011). Hard information commonly refers to financial information (Angilella & Mazzù, 2015), reproduced and frequently verified by the P2P platform, intending to effectively quantify credit risk

[1] See Akerlof (1970)' market for «Lemons».

(Jiang et al., 2018; Petersen, 2004). Soft information is produced by crowdlender-borrower interactions (Kgoroeadira et al., 2019; Liberti & Petersen, 2019), messages framed coming from text descriptions (Dorfleitner et al., 2016; Gao et al., 2018; Larrimore et al., 2011; S. Wang et al., 2016), gender (Chen et al., 2014), race (Pope & Sydnor, 2011), homophily (Burtch et al., 2014; Galak et al., 2011), demography (Alyakoob et al., 2021; C. Wang et al., 2019), and appearance (Duarte et al., 2012), aside others sources of information (Hildebrand et al., 2017; D. Liu et al., 2015; Michels, 2012). In the next section, we address how credit scoring literature may contribute to reducing the asymmetric-information problem and the current limitations in this literature.

2.2. Risk-return measurement

The funding success of crowdfunding campaigns is partly explained by the P2P crowdfunding platform's credit scoring (Basha et al., 2021). However, a strand of literature promotes an open debate on credit scoring adequacy (Bastani et al., 2018; Lyócsa et al., 2022) since credit scores do not offer crowdlenders a global view of the risk-return binomial.

The credit score techniques used by P2P crowdfunding platforms are based on binary metrics (Thomas et al., 2002) that, despite their recurrent use in risk assessment (Finlay, 2010; Stewart, 2011), focus on the mitigation of losses (Thomas, 2000). These techniques focus on aspects such as maximum likelihood and optimal cut to establish the differences between bad and good borrowers, when analysts give greater importance to understanding the classifications' properties (Thomas et al., 2001). This led a stream of credit scoring literature to propose using techniques focused on profitability instead of traditional risk measures (e.g., Lucas, 2001; Thomas, 2000). This stream of research seeks to make credit scoring metrics more aligned with the crowdlenders' intentions and financial return on their capital invested – i.e., their profit (Bastani et al., 2018; Eisenbeis, 1977; Serrano-Cinca & Gutiérrez-Nieto, 2016).

Serrano-Cinca & Gutiérrez-Nieto (2016) address this challenge by focusing on P2P market analysis. The authors rely on the internal rate of return (IRR). Based on a decision tree, their findings show that a profitability score, based on IRR, provides higher returns than one obtained from traditional credit scoring models. Bastani et al. (2018) present empirical evidence that profitability scoring models, which mitigate the imbalanced sample problem, can outperform credit scoring approaches. Xia et al. (2017) also contribute to this open debate by developing a loan valuation model that mitigates the problem of equal costs[2] from default probability analysis. More recently, Lyócsa et al. (2022) proposed an alternative measure of profitability, based on adjusted annualized IRR that assumes that positive cash flows (i.e., capital and/or interest) are annually reinvested. These authors applied different methodologies (i.e., neural networks, random forest, and logistic regressions) and found evidence favoring the measurable benefits of this profitability scoring measure.

However, to the best of our knowledge, the debt-based crowdfunding literature has neglected to use profitability measures that take credit risk into account. In an efficient market, risk is conditional for returns (Lintner, 1965; Markowitz, 1952; Merton, 1973; Sharpe, 1964). Therefore, profitability score models are built under the assumption of maximizing returns with which the highest investment risks may necessarily be associated, thus ignoring the risk propensity of each crowdlender.

We aim to fill this void by putting forward a metric that merges profitability and credit score metrics. Our surmise is that the risk-return binomial may provide crowdlenders evidence on how they should use available information to ground their investment decisions to maximize the return on invested capital, coming from regular interest rates, late payment interest rates, enforced recoveries, advanced payments, and loss given default-- the *profitability metric*--, considering the risk exposure they select from a risk score that expresses the probability of default-- the *credit score metric*.

3. Data, variables, and method

3.1. Data sampling

To provide crowdlenders with the key drivers that favor higher profitability (per unit of risk), we collected data from Lending Club, the largest US P2P lending platform founded in 2007. Lending Club is the first crowdfunding platform to issue an IPO (Initial Public Offering) on the New York Stock Exchange. It runs an *All-Or-Nothing* business model regarding its loan campaigns. Between 2007 and 2018, 2,260,668 loans were granted on this P2P lending

[2] Equal costs problem arises from the assumption that equal errors have the same costs when in fact overvalued loans have much higher costs than undervalued ones (Liu et al., 2018).

platform, with total funding of 34 billion $US. Given the large universe of loan campaigns and to avoid potential computational issues dealing with such a large dataset, we decided to restrict our sample based on several steps. First, we select completed loans, either fully paid or those loans that have already been written off. Second, we excluded loans granted between 2007 and 2009, as they were granted in a test phase of Lending Club. Otherwise, our estimates could be biased due to contextual differences (Jagtiani & Lemieux, 2019). Third, to prevent biased estimations due to outliers, we made a cut-off to the right of the 99.9th percentile (Costa, 2017). Based on these criteria, our global sample includes 1,241,615 loan campaigns granted between 2010-2018 that are in an immutable state (i.e., fully paid or declared as defaulted). Fully paid loan campaigns represent 80.43% and written-off loans are 19.57% of our sample. Finally, to avoid sample-size biases produced by a large sample (M. Lin, Lucas, et al., 2013), we performed a random resampling reducing our analysis to a subsample of 5%, totaling 62,081 observations. To help us in the preparation of this work, we used the statistical software, specialized in econometric analysis, Stata17.

3.2.Variables

In **Table 1** we define the variables used in our study.

Table 1. Variables Definition

Variables	Unit	Measure	Definition
Dependent Variables			
Surplus (per risk)	Ratio (-1 to +1)	Continuous	The difference between the loan return and the average return assigned by the Lending Club, divided by the standard deviation of the grade return.
Improved Score (IP)	(0/1)	Binary	"1" if the loan is better ranked by our profitability scoring model than by the Lending Club grade model, and "0" otherwise.
Independent Variables			
Credit History			
Revolving Line *(RL)*	Ratio (0 to +100)	Continuous	The amount of credit the borrower is using relative to all available revolving credit.
Total lines of credit *(AccLines)*	# Credit lines	Discrete	The total number of credit lines currently in the borrower's credit file.
Credit Inquiries	# Inquiries	Discrete	Credit inquiries in the last 6 months.
Derogatory public records *(PR)*	# Records	Discrete	Number of derogatory public records.
Wealth			
log (Annual Income) *(Ainc)*	log (USD)	Continuous	The logarithm of one plus the self-reported annual income, provided by the borrower during registration.
Employment Length *(Emp)*	# Years	Discrete	Number of years (0 if <1 year; 10 if >=10 years).
Indebtedness			
Indebtedness *(Indeb)*	Ratio (0 to 100)	Continuous	Borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested Lending Club loan, divided by the borrower's self-reported monthly income.
Loan			
log (Loan Amount)	log (USD)	Continuous	Is the logarithm of the amount requested of the Loan in $US.
Control Variables			
Lending Club Grade	Grade (A to G)	Ordinal	A set of seven binary variables for Grades provided by Lending Club platform, based on credit risk. [Grade A: lower risk; Grade G: higher risk]

3.2.1. Dependent variables

As pointed out, we aim to analyze whose factors contribute to maximizing the return on invested capital considering the risk exposure they choose. To achieve this goal, we propose two variables that intertwine the yield effectively obtained weighted by credit risk estimated by the Lending Club platform: i) *surplus* (per risk), and ii) *improved score.*

Surplus (per risk) measures the excess return over the average return on investment for each specific risk level, captured by Lending Club (LC)'s Grade, as follows:

$$\text{Surplus } (per\ risk) = \frac{\text{Profitability}_{\text{i}} - \text{Mean Profitability by LC}'\text{Grad }_{\text{i}}}{\text{Standard Deviation by LC}'\text{Grad }_{i}} \qquad \text{eq. (1)}$$

Where:

$$Profitability\ score = -1 + \left(\frac{Total\ Payment}{Loan\ amount}\right)^{1/Effective\ Maturity\ (in\ years)}$$

eq. (2)

Relying on Lending Club grades, we can measure the volatility of earnings by each grade (through standard deviation) and the average return on credit risk. See **Table A1**, in an appendix, for summary statistics on the profitability by Lending Club grade. The metric *Surplus* (per risk) allows us to adjust the profitability score for risk means effects and standardize it within each LC grade. Thus, this measure offers the possibility to know how much crowdlenders effectively lose or gain annually relative to similar investments, not disregarding the analysis of risk aspects such as prepayments, coercive recoveries, and late payment interest – three of the six main types of risk components in the P2P lending (Z. Wei & Lin, 2017) – captured by our first profitability score measure – *Surplus* (per risk). Hence, the *Surplus* (per risk) is a continuous variable that encapsulates credit risk, addressing crowdlenders' concerns about both profitability and risk. By offering a picture of which loans have a greater added value per risk unit, we posit that the *Surplus* (per risk) is an alternative profitability score metric to the body of knowledge regarding profitability analysis (e.g., Serrano-Cinca & Gutiérrez-Nieto, 2016).

The Lending Club platform provides seven loan grades from A (best grade, lower risk) to G (worst grade, higher risk) obtained from FICO (Fair Issac Credit Organization) score. Besides the FICO score, P2P platforms consider other factors, such as the number of recent credit inquiries, duration of credit history, total open credit account, currently open credit lines, and revolving line usage, to provide the credit score and to set interest rates. We propose an ordinal classification of loans based on our profitability score. Based on this indicator, we classify each loan campaign based on profitability scores from A to G similarly to Lending Club grades.

To assign the profitability score to each campaign, we self-imposed the restriction of maintaining an equal distribution of observations by risk levels between the Lending Club model and our profitability score model. This restriction ensures, for example, a match between the number of campaigns rated as *Grade A* by Lending Club and the number of campaigns rated as *Score A* by our profitability scoring model[3]. Then, we compare the ranking obtained from our profitability score (considering the return per risk unit)[4] and the Lending Club model. We rely on this comparison to construct a binary variable called *Improved score* (*IP*) that takes the value 1 if the loan campaign is better ranked by our profitability scoring model than by Lending Club grade, and 0 otherwise.

3.2.2. Independent variables

We rely on four categories of loan performance determinants to provide information about how crowdlenders must use available information to maximize *Surplus* (per risk) and the likelihood of *Improved score* based on their risk exposure: i) credit history (Emekter et al., 2015; Serrano-Cinca et al., 2015; Serrano-Cinca & Gutiérrez-Nieto, 2016; Zhou et al., 2018); ii) borrower's financial wealth, iii) indebtedness (Emekter et al., 2015; Serrano-Cinca et al., 2015); as well as iv) loan size. Borrower's credit history includes four variables: *revolving line* (*RL*); *Inquiries* in the last 6 months; the total number of credit lines (*AccLines*), and *derogatory public record* (*PR*). As proxies for borrowers' financial wealth, we use the annual income of the individual (*Ainc)* (Berger & Gleisner, 2009; Greiner & Wang, 2010) and the length of their employment (*Emp*) (Railiene, 2018). We measure indebtedness (Indeb) using the debt/income ratio. Finally, we test the loan *Amount* effect (Railiene, 2018; Lin, 2017).

3.2.3. Control variables

We control the credit *Grade* in P2P lending, attributed by Lending Club, using a set of seven binary variables for each grade that guides interest rates negotiation between Lending Club

[3] This decision was taken in such a way that the subsequent comparison between models would be as fair as possible.
[4] The notation is as follows: the best-rated loans receive an A, which means that the loans with the highest profitability will have the highest grades, and the worst loans with the lowest profitability will receive a G in our model.

and crowdlenders. The *Grade* is a variable that contains information paraphernalia, such as the FICO score, credit history, and the number of open accounts. Furthermore, the *Grade* is commonly used in the credit scoring literature in predicting loan default (Cai et al., 2016; Carter et al., 2014; Emekter et al., 2015; Feng et al., 2015), as well as a control variable, namely for profitable scoring models (e.g., Serrano-Cinca & Gutiérrez-Nieto, 2016).

3.3.Method

To examine the characteristics that crowdlenders should focus on to increase their profitability per unit of risk on their P2P lending crowdfunding investments, we run a linear model (eq. 3) and a logistic model (eq. 4) as follows:

$$\text{Surplus per risk} = \alpha_i + \beta_{1i}\text{RL} + \beta_{2i}\text{AccLines} + \beta_{3i}\text{Inquiries} + \beta_{4i}\text{PR} + \beta_{5i}\ln(\text{Ainc}) + \beta_{6i}\text{Emp} + \beta_{7i}\text{Indeb} + \beta_{8i}\log(\text{Amount}) + \sum_{k=9}^{14}\beta_{ki}Grade + \varepsilon_i \qquad \text{eq. (3)}$$

$$\log\frac{p_{IP}}{1-p_{IP}} = \alpha_i + \beta_{1i}\text{RL} + \beta_{2i}\text{AccLines} + \beta_{3i}\text{Inqueries} + \beta_{4i}\text{PR} + \beta_{5i}\ln(\text{Ainc}) + \beta_{6i}\text{Emp} + \beta_{7i}\text{Indeb} + \beta_{8i}\log(\text{Amount}) + \sum_{k=9}^{14}\beta_{ki}Grade \qquad \text{eq. (4)}$$

Where p is the probability of the i^{th} borrower having a better ex-post performance (calculated by the effective profitability score as described in subsection 3.2.) than that estimated by the grade assigned ex-ante by the platform.; ε denotes the error term. To exclude some potential confounding factors, each regression controls for time (i.e., year) fixed effects.

3.4. Descriptive statistics

Table 2 reports the descriptive statistics of our random sample[5].

Table 2. Descriptive Statistics **(random sample)**

Variables	Obs.	Mean	Std. Dev	Min	Max.
Dependent Variables					
Surplus *(per risk)*	62,081	0.006	0.987	-7.14	1.37
Improved score *(IP)*	62,081	0.373	0.483	0	1
Independent Variables					
Credit History					
Revolving Line *(RL)*	62,081	52.30	24.36	0	102.4
Total lines of credit *(AccLines)*	62,081	25.01	11.73	2	80
Credit Inquiries	62,081	0.650	0.926	0	5
Derogatory public records *(PR)*	62,081	0.202	0.529	0	6
Wealth					
Annual Income *(Ainc) in $USD*	62,081	76,590.56	45,841.13	4,800	556,000
Employment Length *(Emp)*	62,081	5.961	3.68	0	10
Indebtedness					
Indebtedness *(Indeb)*	62,081	18.13	8.44	0	65.39
Loan					
Loan Amount *in $USD*	62,081	14,612.33	8,723.31	1,000	40,000

See Table 1 for the definition of the variables.

The final sample includes 62,081 loans; 11,437 (18.42%) generated losses, and 50,644 (81.58%) generated profits. More than 37% of loans had a better performance per unit of risk than expected from the risk assessment made by the P2P lending platform and provided as credit-risk information to potential crowdlenders. On average, the revolving lines utilization rate is 52%, and borrowers have a credit history with an average of 25 credit lines, with a minimum of 2 credit lines and a maximum of 80 credit lines. On average, each borrower has 0.65 credit inquiries and 0.2 derogatory public records. Regarding the financial situation, on average, a borrower has an annual income of $76,590.56, and has been working for at least 6 years, with debt representing a monthly effort of 18% on his income (excluding Lending Club debt and mortgages). The average amounts borrowed are $14,612.33, with the minimum and maximum amount set by the Lending Club platform being $1,000 and $40,000, respectively.

[5] All variables in this have a right cut of 99.9%, except for variables whose maximum value is according to the delimitation defined by the Lending Club platform (i.e., Employment Length and Loan Amount). This option was taken according to the definition of outliers made by some scholars (e.g., Costa, 2017).

Table 3 reports univariate tests. Column I report the statistics for the subsample of loans that would be benefited from our metrics with better performance than that pointed out by credit scoring; Column II report the statistics for the remaining loans. Column III report univariate tests for standard deviation (*Levene test*) and means differences (*t-test*).

We found evidence that lenders with profitability grade higher than Lending Club's grade provide credit to borrowers with greater use of the revolving lines, fewer credit accounts on file, more inquiries and derogatory public records, lower annual income, and higher indebtedness, and higher loan amount, assuming a 1% statistical significance (p-value < 0.01). Hence, riskier and opaque borrowers seem to prevail among lending-crowdfunding investments that perform better than the Lending club's credit score predicted.

The correlation matrix, reported in Table A2, in Appendix, does not reveal any high pairwise correlations between non-binary covariates, which suggests that multicollinearity appears not to be an issue in our study.

Table 3. Univariate tests

Variables	Column I					Column II					Column III – Tests		
	Did not Improved					*Improved*					*Levene*	*t.test*	
	Obs.	Mean	Std. Dev	Min	Max.	Obs.	Mean	Std. Dev	Min	Max.	p-value	Diff.	p-value
Independent Variables													
Credit History													
Revolving Line	38,861	49.638	24.231	0	102.3	23,220	56.767	23.930	0	102.4	**	-7.128	***
Total lines of credit *(AccLines)*	38,861	25.146	11.653	2	79	23,220	24.780	11.869	2	80	***	0.366	***
Credit Inquiries	38,861	0.551	0.847	0	5	23,220	0.817	1.026	0	5	***	-0.266	***
Derogatory public records *(PR)*	38,861	0.187	0.513	0	6	23,220	0.229	0.555	0	6	***	-0.042	***
Wealth													
Annual Income *in $USD*	38,861	78,128.9	46,623.03	4,800	556,000	23,220	74,015.98	44,383.67	8,000	550,000	***	4112.92	***
Employment Length	38,861	5.939	3.693	0	10	23,220	5.997	3.681	0	10		-0.058	*
Indebtedness													
Indebtedness	38,861	17.506	8.215	0	64.04	23,220	19.188	8.727	0	65.39	***	-1.682	***
Loan													
Loan Amount *in $USD*	38,861	14,020.07	8,318.15	1,000	40,000	23,220	15603.54	9278.224	1,000	40,000	***	-1583.47	***

*** p-value <0.01; ** p-value <0.05; * p-value <0.1. See Table 1 for the definition of the variables.

4. Results

4.1. Main Findings

The estimates for profitability *Surplus (per risk)* obtained from the OLS linear model (eq. 3) is reported in **Table 4**. **Table 5** report the estimates of the probability of *Improved score* based on a logit model (eq. 4). The results are presented progressively, starting from a model containing only the control variables and time-fixed effects[6] (Column I). Column II adds credit history measures. Columns III and IV include measures of borrower's financial wealth and indebtedness, respectively. Column V report the results for the partial model, including loan characteristics. Finally, the full model is reported in Column VI.

Table 4 reports a negative relationship between the number of credit *Inquiries* and profitability *Surplus* per unit of risk (Column VI: p-value < 0.01), and a positive relationship between the total *number of credit lines* and profitability surplus per unit of risk (Column VI: p-value < 0.01). We do not find any statistically significant effects of revolving lines or derogatory public records on the profitability surplus per risk (p-value > 0.1). However, Table 5 shows a negative effect of revolving lines on the probability of improving the score (Column VI: p-value< 0.01). We also find evidence of a positive effect of annual *income* and *employment length* on both the profitability *Surplus* per risk (Table 4, Column VI: p-value<0.01) and the probability of improving the score (Table 5, Column VI: p-value<0.01). Finally, borrowers' *indebtedness* and loan *Amount* reduce the ability to have a better performance than that signaled by Lending Club grades (Table 4, Column VI, p-value<0.01).

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[6] We analyze a time span (2010-2018) during which financial markets experiences various shocks. The first half of this period was marked by an atypical period in the economy due to the economic-financial crisis (*The Fed - Monetary Policy*, 2014). This period is followed by a higher-than-expected increase in interest rates (Bertsch et al., 2016). As portrayed in the financial literature, these contexts are challenging for borrowers with increases in loan spreads (Gertler & Karadi, 2015) as in the risk-free rate (Kuttner, 2001). Thus, one would expect consequences in the P2P lending market.

Table 4. OLS estimation (Robust standard errors). Dependent variable: *Surplus per Risk Unit*

	Control	Credit History	Wealth	Indebtedness	Loan	Full
Variables	I	II	III	IV	V	VI
Independent Variables						
Credit History						
Resolving Line		0.000				0.000
		(0.000)				(0.000)
Total lines of credit		0.001				0.001***
		(0.000)				(0.000)
Credit Inquiries		−0.025***				−0.034***
		(0.005)				(0.005)
Derogatory public records		0.004				−0.009
		(0.008)				(0.008)
Wealth						
Annual Income			0.052***			0.093***
			(0.008)			(0.010)
Employment Length			0.005***			0.006***
			(0.001)			(0.001)
Indebtedness						
Indebtedness				−0.005***		−0.004***
				(0.000)		(0.001)
Loan						
Loan Amount					−0.055***	−0.095***
					(0.006)	(0.007)
Control Variables						
Lending Club Grade (Base Category: A)						
B	−0.015	−0.011	−0.007	−0.006	−0.018	0.006
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
C	0.011	0.020	0.023*	0.027**	0.010	0.054***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
D	−0.016	−0.004	−0.004	0.005	−0.012	0.049***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)
E	−0.027	−0.012	−0.016	−0.003	−0.014	0.054***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.019)
F	−0.061**	−0.043	−0.052*	−0.037	−0.041	0.033
	(0.028)	(0.029)	(0.028)	(0.028)	(0.028)	(0.029)
G	−0.046	−0.023	−0.035	−0.016	−0.020	0.075
	(0.050)	(0.051)	(0.050)	(0.051)	(0.051)	(0.051)
Intercept	−0.038	−0.032	−0.643***	0.016	0.457***	−0.208*
	(0.042)	(0.044)	(0.099)	(0.043)	(0.067)	(0.109)
Year Fixed Effects	Included	Included	Included	Included	Included	Included
Observations	62,081	62,081	62,081	62,081	62,081	62,081
Adjusted R^2	0.011	0.011	0.012	0.013	0.012	0.017
VIF						
Max (excluding control variables effects)		1,16	1,05	1,05	1,03	1,64
Mean		1,085	1,035	1,050	1,03	1,265

Robust standard errors between branches; *** p<0.01, ** p<0.05, * p<0.1. See Table 1 for variables definition.

Table 5. Logit estimation (Robust standard errors). Dependent variable: *Improved Score*

	Control	Credit History	Wealth	Indebtedness	Loan	Full
Variables	**I**	**II**	**III**	**IV**	**V**	**VI**
Independent Variables						
Credit History						
Resolving Line		-0.002***				-0.002***
		(0.001)				(0.001)
Total lines of credit		0.006***				0.006***
		(0.001)				(0.001)
Credit Inquiries		-0.023*				-0.044***
		(0.012)				(0.012)
Derogatory public		-0.004				-0.029
		(0.021)				(0.021)
Wealth						
Annual Income			0.185***			0.238***
			(0.023)			(0.030)
Employment Length			0.008**			0.009***
			(0.003)			(0.003)
Indebtedness				-0.010***		-0.009***
Indebtedness				(0.001)		(0.002)
Loan						
Loan Amount					-0.063***	-0.172***
					(0.017)	(0.020)
Control Variables						
Lending Club Grade (Base Category: A)						
B	2.629***	2.664***	2.657***	2.647***	2.626***	2.713***
	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)	(0.213)
C	6.725***	6.780***	6.769***	6.760***	6.726***	6.881***
	(0.209)	(0.209)	(0.209)	(0.209)	(0.209)	(0.210)
D	7.049***	7.112***	7.099***	7.097***	7.056***	7.254***
	(0.210)	(0.210)	(0.210)	(0.210)	(0.210)	(0.211)
E	7.609***	7.675***	7.654***	7.664***	7.626***	7.846***
	(0.212)	(0.213)	(0.212)	(0.212)	(0.212)	(0.213)
F	8.451***	8.519***	8.490***	8.505***	8.477***	8.707***
	(0.227)	(0.228)	(0.228)	(0.227)	(0.227)	(0.229)
G	9.539***	9.622***	9.585***	9.606***	9.571***	9.850***
	(0.343)	(0.344)	(0.343)	(0.344)	(0.343)	(0.345)
Intercept	-6.665***	-6.695***	-8.770***	-6.571***	-6.095***	-7.771***
	(0.242)	(0.245)	(0.359)	(0.243)	(0.286)	(0.381)
Year Fixed Effects	Included	Included	Included	Included	Included	Included
Observations	62,081	62,081	62,081	62,081	62,081	62,081
Mcfadden Pseudo R^2	0.012	0.014	0.018	0.017	0.013	0.019

Robust standard errors between branches; *** p<0.01, ** p<0.05, * p<0.1. See Table 1 for variables definition.

The results on the set of control variables *Grade* also suggest statistical significance differences among grades, particularly for the logit estimation (Table 5).

The results reported in Table 5 are divergent from univariate statistics (Table 3). This confirms that there are confounding factors ignored by univariates statistics that must be considered when estimating the association between the probability of improved grade and each explanatory variable.

4.2. Supplementary analysis

Our previous results on *Surplus per risk* are aligned with the credit scoring literature, namely that related to a credit default. To check the robustness of our results, in this subsection, we extend the analysis of the determinants of *surplus per risk* for risk subsamples built from Lending Club grades. Following the risk grouping made by Nigmonov et al. (2022), we group each grade into three intervals of risk: low risk (Grade A and B), medium risk (Grade C, D and E), and high risk (Grade F, G). The results are reported in Table A3 in the appendix.

The results show similar associations between *Surplus per risk* and the independent variables among low-risk and medium-risk subsamples, except for *Revolving Lines* and *Derogatory public records* that turn out to be negatively related to *Surplus per risk*. The Wald test also shows that the effect of the annual *income* and loan *Amount* on the *surplus per risk* is statistically higher among medium-risk loan campaigns than for low-risk loan campaigns. Among riskier loan campaigns, the *Surplus per risk* is only negatively associated with borrowers' *indebtedness* and loan *amount*, which is in line with debt seniority (Bolton & Jeanne, 2009; Diamond, 1993) and moral hazard arguments. Credit history and borrowers' financial wealth appear not to exert a significant effect on profitability relative to their riskier pairs.

5. Discussion

Our evidence on the determinants of the surplus of return per risk and the likelihood of improved grade parallels the credit default literature. Our results show that borrowers with better credit history offer better profitability surplus weighted by risk, similarly to previous research pointing to the importance of the best track record to mitigate the probability of default (e.g., Serrano-Cinca et al., 2016; Emekter et al. 2015; Cinca et al., 2015). Crowdlenders investing in crowdfunding campaigns promoted by borrowers with higher incomes and job experience tend to achieve higher profitability in their investments in P2P lending crowdfunding campaigns. This evidence is also in line with literature on the probability of default (e.g., Berger & Gleisner, 2009; Railiene, 2018). Emekter et al. (2015) postulate that borrowers with a greater weight of debt in their income tend to be more likely to default on their loans. Our results support this idea by showing that borrowers with lower indebtedness offer greater profitability (Table 4). Smaller loans are potentially more profitable, in line with Railiene (2018) and Lin (2017). Lenders that grant lower amounts are less exposed to default.

Overall, our results show that the higher returns, usually provided by riskier loans, do not compensate for the higher risk involved. Higher credit risk loans were loss generators for crowdlenders, so they should focus on investing on less risky borrowers. In turn, that investments will promote a sustainable development in debt-based crowdfunding platforms (Berkovich, 2011; Emekter et al., 2015).

Our findings suggest that traditional approaches to loan performance reflect the main risks faced in this P2P lending market, including credit risk (Lessman et al., 2015) and loss-given default. Therefore, despite their criticisms, traditional credit score models seem more efficient than the profitability literature argues for lower-risk campaigns. Using a variable that considers the binomial risk-return, we offer evidence aligned to those provided by studies that focused on the analysis of the probability of default (a variable commonly used in traditional models), thus demonstrating that the non-measurement of profitability may not be a problem of high implication. One possible reason for these results is high losses in the event of default. For example, nearly 50% of loans are granted with a maturity of 36 months or 60 months default within the first 12 months (Jagtiani & Lemieux, 2019). Thus, in our risk-return model, the probability of default and/or loss given default outweighs the potential for profitability. Therefore, the greater risk, the lower the profitability *surplus per risk*, even if more risk means higher interest rates.

However, for riskier campaigns, we find that credit history and borrowers' financial wealth do not significantly affect the profitability surplus per risk. Thus, the literature on the probability of default only partially explains the financial performance when considering the binomial risk-return for riskier loan campaigns.

6. Conclusions

P2P lending markets underwent rapid development, offering an alternative financing strategy for borrowers facing credit rationing from traditional financial markets. For lenders, these markets provide risk diversification opportunities. Despite the intermediation of P2P platforms, crowdlenders face an information asymmetry problem that may reduce the profitability of their investments in crowdfunding projects through loan campaigns. Credit scoring models are usually pointed out as a possible solution to this problem. However, profitability literature has pointed out several critics and limitations to the credit score as a decision tool for non-institutional crowdlenders (e.g., Bastani et al., 2018; Fitzpatrick & Mues, 2021; Guo et al., 2016; Lyócsa et al., 2022; Serrano-Cinca & Gutiérrez-Nieto, 2016). One of the research gaps on which we focus refers to the fact that traditional models might ignore that the profitability of an investment depends on the lender's risk appetite. To fill this gap, we use data from a Lending Club, a US P2P lending crowdfunding platform, and merge credit scoring (i.e., default likelihood) and profitability literature to analyze *what the characteristics that crowdlenders should focus on to increase their profitability per unit of risk on P2P lending crowdfunding are?* With this, we intend to compare our results with the results that come from the credit scoring literature that focuses on the analysis of traditional models based on the probability of default to understand the impact of not analyzing the potential return on loans – a problem mentioned by the profitability literature about traditional models.

Our results show that the higher returns, which riskier loans could provide, do not compensate for the higher risk involved. Among low-risk and medium-risk campaigns, crowdlenders should opt for smaller loans with higher annual incomes, greater job stability, lower indebtedness, and overall better credit history. Our results corroborating the results of the credit scoring literature suggest, therefore, that traditional loan performance approaches reflect not only the main risks faced in this market, including credit risk (Lessman et al., 2015) and loss given default, but they also end up predicting the return very well for low risky campaigns. However, credit history and borrowers' financial wealth do not significantly affect the profitability of riskier campaigns. This result opens a research call for future research avenues.

One of the limitations of our study is that we only focus on hard information. Soft information is also proven relevant to identify better investments (Claessens et al., 2018; Dorfleitner et al., 2016; Jagtiani & Lemieux, 2018; Morse, 2015), thus, improving efficiency risk management in P2P loan crowdfunding. However, due to data limitations (e.g., we do not have the textual descriptions that borrowers made at the time of applying for funding, their photographs, ethnicity, and gender, among other variables already identified in the literature that focus on the impact that soft information has), we do not include soft information in our analysis. Despite having a lower explanation power than hard information on investment performances (Stevenson et al., 2021), we acknowledge that the absence of soft information in our model is a relevant limitation of this study. Another limitation may be the fact that we focus on the analysis only on one platform, limiting the repercussion of the results for other contexts. Further research should extend our model to test the role of soft information when predicting the surplus per risk, especially in riskier loan campaigns, and also trying to focus analysis on other platforms.

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Appendix

Table A1. Profitability by Lending Club Grade

Grade	Obs	Mean	Std. dev.	Min	Max
A	10,972	0.022	0.137	−1	0.171
B	18140	0.008	0.214	−1	0.274
C	17,723	−0.025	0.292	−1	0.331
D	9,093	−0.045	0.340	−1	0.389
E	4250	−0.075	0.382	−1	0.383
F	1,453	−0.118	0.435	−1	0.382
G	450	−0.214	0.489	−1	0.383

Table A2. Correlation Matrix for continuous covariates

Variables	–	1	2	3	4	5	6	7	8	9	10
Dependent Variables											
Surplus per Risk Unit	1	1.0000									
Improved Grade	2	0.362*	1.000								
Independent Variables											
Credit History											
Resolving Line	3	0.022*	0.141*	1.0000							
Total lines of credit	4	0.007	–0.017*	–0.108*	1.000						
Credit Inquiries	5	–0.014*	0.139*	–0.086*	0.146*	1.0000					
Derogatory public records	6	–0.006	0.037*	–0.081*	0.016*	0.072*	1.000				
Wealth											
Annual Income	7	0.026*	–0.041*	0.057*	0.253*	0.045*	–0.009	1.000			
Employment Length	8	0.0255*	0.008	0.034*	0.102*	–0.003	0.036*	0.089*	1.000		
Indebtedness											
Indebtedness	9	–0.045*	0.093*	0.176*	0.236*	–0.003	–0.041*	–0.215*	0.036*	1.000	
Loan Characteristics											
Loan Amount	1	–0.024*	0.086*	0.112*	0.210*	–0.016*	–0.073*	0.453*	0.089*	0.039*	1.000

* p<0.01. See Table 1 for variables definition.

Table A3. OLS estimation (Robust standard errors). Dependent variable: Surplus per Risk

	Grade			
	Low Risk (Grade A/B)	Medium Risk (Grade C/D/E)	High Risk (Grade F/G)	Wald Test of equality of coefficients: Chow test chi-square statistic
Independent Variables				
Credit History				
Resolving Line	-0.001**	-0.000	-0.001	1.50
	(0.000)	(0.000)	(0.001)	
Total lines of credit	0.002***	0.002***	0.003	1.74
	(0.001)	(0.001)	(0.002)	
Credit Inquiries	-0.028***	-0.027***	-0.020	0.16
	(0.008)	(0.006)	(0.020)	
Derogatory public	-0.023*	-0.022**	0.056	3.68
	(0.012)	(0.010)	(0.043)	
Wealth				
Annual Income	0.056***	0.109***	0.052	7.42**
	(0.014)	(0.014)	(0.064)	
Employment Length	0.003*	0.007***	0.011	3.17
	(0.002)	(0.002)	(0.006)	
Indebtedness				
Indebtedness	-0.004***	-0.005***	-0.005*	0.23
	(0.001)	(0.001)	(0.003)	
Loan Characteristics				
Loan Amount	-0.054***	-0.130***	-0.202***	35.88***
	(0.010)	(0.009)	(0.046)	
Years Effect Fixed	Included	Included	Included	
Intercept	-0.175	0.023	1.742***	
	(0.150)	(0.148)	(0.646)	
Observations	29,112	31,066	1,903	
Adjusted R^2	0.008	0.028	0.049	

Robust standard errors between branches; *** p<0.01, ** p<0.05, * p<0.1. See Table 1 for variables definition.