Concept of Peer-to-Peer Lending and Application of Machine Learning in Credit Scoring

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ABSTRACT

Numerous applications of AI are found in the banking sector. Starting from the front-office, enhancing customer recognition and personalized services, continuing in the middle-office with automated fraud-detection systems, ending with the back-office and internal processes automatization. In this paper we provide comprehensive information on the phenomenon of peer-to-peer lending in the modern view of alternative finance and crowdfunding from several perspectives. The aim of this research is to explore the phenomenon of peer-to-peer lending market model. We apply and check the suitability and effectiveness of credit scorecards in the marketplace lending along with determining the appropriate cut-off point.
We conducted this research by exploring recent studies and open-source data on marketplace lending. The scorecard development is based on the P2P loans open dataset that contains repayments record along with both hard and soft features of each loan. The quantitative part consists in applying a machine learning algorithm in building a credit scorecard, namely logistic regression.

JEL Classification: G21; C25

Keywords: artificial intelligence, peer-to-peer lending, credit risk assessment, credit scorecards, logistic regression, machine learning.

1. INTRODUCTION

The recent explosive growth of brand-new alternative financial possibilities has brought about a lot of discussions and studies. One of such possibilities is the peer-to-peer alternative finance sector. The primary focus has been put on the analysis of a possible expansion of the peer-to-peer (P2P) finance industry with sequential inversion of the existing structural and institutional organization of banking. There are numerous instances of how peer-to-peer technology may

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affect a particular industry. Considerable changes have already occurred in lodging, file sharing, multimedia, etc. A decentralized network of credit relations increasingly captures the credit market and challenges traditional banking pillars. P2P lending is characterized by the improvement of service and higher economic efficiency. On the other hand, P2P technology brings about various risks that have to be addressed.

In our paper we aimed to understand the structure and key features of a peer-to-peer lending market model, its role in financial intermediation, and investigate the main advantages and drawbacks of marketplace lending. Once we develop a clear understanding, the objective is to apply and check the suitability and effectiveness of credit scorecards in the marketplace lending along with determining the appropriate cut-off point.

The research is conducted by exploring recent studies and open-source data on marketplace lending. The scorecard development is based on the P2P loans open data set that contains repayments record along with both hard and soft features of each loan. The quantitative part consists in applying a machine learning algorithm in building a credit scorecard, namely logistic regression. The objective is to select, through descriptive and quantitative analysis, the best features that allow differentiating the loan performance in the marketplace lending environment and process the data, followed by scorecard construction and quality assessment.

The research paper is divided into three parts, each part having its particular objectives. Section 2 of the research is dedicated to developing a broad picture of the traditional financial system, as well as exploring the origins, explaining the structure and features of marketplace lending. The emphasis is put on the general mechanism of the platform's intermediation. Section 3 is intended to study the P2P lending system from the perspective of an end-user, along with the determination of risks involved in marketplace lending and an overview of current regulatory frameworks and practices. As an empirical part of the chapter, breakdowns of the alternative finance market in the European Union and in the United Kingdom are prepared. Section 4 contains an analysis of credit risk in marketplace lending. A credit scorecard is created based on the Logistic Regression, utilizing the best practices of variable processing and modelling. The last section number 5 provides conclusion of the paper.

2. BANKING SYSTEM AND MODERN LENDING

2.1. Traditional Banking and Modern Lending

Banking has its roots deep in the past. The evolution of the banking system intensely changed and created an intricate structure of services offered by the banking sector and banking structure itself in the process of time. Historically, the first and the only objective of a bank was to securely store consumer savings. The primary function of a contemporary bank is still accepting deposits from legal entities as well as individuals, acting as a borrower; and providing loans on a time-interest basis, acting as a lender, which enables a bank to perform transformations of savings to investments, in other words, asset transformation.

These days the financial system performs this fundamental function. It serves as a platform for funds channeling: those who have a surplus of their funds (savers) may lend them to spenders, i.e., those who are willing to borrow money. This fundamental mechanism may be of either direct or indirect nature. In the first case, funds are transferred from lenders directly to the financial market and channeled via financial securities to borrowers as a claim for their future income. Thus, securities are assets for creditors and liabilities for debtors. In the latter case, financial intermediaries step in, savers lend their funds to financial institutions, and they, in turn, may lend these funds via financial market or directly to borrowers. Above-mentioned relations foster the

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productivity of the economic system, solving the problems of inefficient capital allocation and lack of liquidity.

Initially, the term 'peer-to-peer' (P2P) was created to indicate the process of direct interaction between two parties without the need for the central intermediary being involved. The name originally described a computer network system in which any computer may act both as a server or as a client relative to other machines operating in this network; therefore, a centralized server was no longer required for the network functioning. A sequence of information technology innovations that took place in the first decade of the 21st century led to an enormous expansion of broadband internet usage and peer-to-peer (also interpreted as people-to-people) technology implementation in diverse ways. The P2P technology made a colossal impact of P2P on file sharing. For instance, the appearance of BitTorrent is one of the most popular communication protocols used in the distribution of data and electronic files over the internet. Digitalization created a framework for numerous platform-based markets and aggregators that perform as instruments for buyers and sellers of various goods and services, where main determinants of prices are genuinely demand and supply in the long run and the auction processes or fixed-price offers in a short run. This changed numerous market sectors, including accommodation services (Airbnb, launched in 2008), transport (Uber, launched in 2009), etc. Similarly, technological progress opened new horizons and opportunities for the financial sector by smoothing out the distance and reducing obstacles to access, allowing the market to expand and new services to arise. The FinTech expansion brought in a disturbance to the financial intermediation market in the form of brand-new crowdfunding projects and ventures.

Initially, the P2P lending market consisted of individual investors and small businesses. Over time, large firms and investors have entered the market, and the term "P2P lending" has become less descriptive. The new name – marketplace lending – has come into use. There are some misunderstandings related to the usage of these two terms. However, they are mostly interchangeable and stand for fundamentally the same mechanism that allows matching lenders and borrowers directly through online services. The only difference is in parties involved. In P2P lending, primarily individuals and small businesses are engaged in the lending cycle, whereas in marketplace lending institutional investors enter the market. Nowadays, the marketplace lending may be broken up into consumer lending, business lending, and property lending. Consumer lending constitutes a significant part of marketplace lending and is granted for various purposes, including debt consolidation, credit card refinancing, home improvements, and major purchases. Business lending is actively utilized by manufacturing and engineering companies, as well as businesses operating in transport and utilities. Property lending firms provide services and products and flexible financing models starting from bridging finance to commercial and residential mortgages, and construction and development investment opportunities. The very first P2P lending platforms were Zopa, established in the UK in 2005[2] and Prosper, launched in 2006 in the US These companies laid the foundation for the development of the decentralized marketplace, which enables borrowers and lenders to deal directly with each other without the involvement of a mediator, broker, or intermediary. Zopa is now one of the largest European P2P lending platforms, having the market share on the UK market of around 28.79%.[3]

It is, however, of fundamental importance to take into account that different government regulations apply to P2P platforms and to banks. Generally, fewer regulatory requirements allow broader operational scope at the lower costs. This, however, generates additional risk.

[2] BBC UK. (2005). Q&A: Online lending exchange.

[3] P2PMarketData. (2019). Accessed October 31, 2019. https://www.p2pmarketdata.com.

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3. LITERATURE REVIEW

3.1. Credit Grade Assigned by a Platform Reduces Information Asymmetry

Recent studies have covered the topic of risk of credit default in marketplace lending. Studies included analysis of loan/borrower characteristics that affect the loan performance. The analysis of 143,654 matured P2P loans funded in 2012–2013 did not reject the hypothesis stating that the credit grade assigned by a platform reduces information asymmetry (Möllenkamp, 2017). That study, entitled *Determinants of Loan Performance in P2P Lending*, found that credit grade is a prevalent determining factor of bad debt, hence a lower credit grade increases the probability of bad debt. Factors that were positively correlated with high loan performance included annual income, debt-to-income ratio, and inquiries in the last six months. The inverse relationship was found between the loan amount and debt performance. The paper *Determinants of Default in P2P Lending* (Serrano-Cinca et al., 2015) studied the determining factors within each credit grade. As in the previous research, annual income, debt-to-income ratio, and inquiries in the past two years along with "Credit Card" and "Small Business" loan purposes were once again found as efficient predictors for each grade class. Also, revolving credit utilization and delinquency in the past two years are useful in the low-risk category (grade A), whereas the length of credit history has shown high efficiency in high-risk (grade C) loan class.

The problem of information asymmetry is addressed in *Disrupting Finance: FinTech and Strategy in the 21st Century* (Lynn et al., 2018). A borrower has nearly complete information, while the information provided by the platform guides the investor most of the time. The book highlights the importance of credit grade assigned by the platforms' preliminary screening based on hard information[4] (i.e., debt-income ratio, number of opened credit lines, etc.). It is argued that for better information disclosure and improvement in decision-making credit scores should be used instead of credit grades, since the latter may not accurately serve as estimates of debtors' creditworthiness.

An empirical investigation of a large sample of PRC's P2P platform containing data on repayment records included in the working paper entitled *Adverse Selection and Credit Certificates: Evidence From a P2P Platform* (Hu et al., 2019) has shown that borrowers tend to attract lenders with high-grade certificates. Certificates are a technique of signaling the presence of information asymmetry. In theory, such licenses have been designed to distinguish borrowers with lower delinquency. Consequently, more funds are loaned to borrowers holding certificates. Despite this, the study has shown that borrowers holding certificates with higher grades have a propensity to higher ex-post delinquency and default rates. The research on **investors** is mainly focused on investment decisions and learning behavior. *A Trust Model for Online Peer-to-Peer Lending: A Lender's Perspective* study (Chen et al., 2014) examined the trust of lenders in borrowers and their willingness to lend via P2P lending intermediaries. The first finding was that the platform's level of service quality and protection significantly affects the lender's trust in the intermediary. The second conclusion was that *"The information quality of borrowers' loan requests is the most important factor influencing lenders' trust in borrowers…"* (Chen et al., 2014). Investors who have suffered financial loss are more liable to herd, thereby lend higher amounts to loan requests that are highly trusted by other creditors (Gonzalez, 2018). The research on the investor side carried out by (Vallée & Zeng, 2019) has confirmed that advanced investors tend to assess loans in a different way than those who are less sophisticated. Moreover, it was proven on the empirical data, that there is a tendency of outperforming by more sophisticated creditors when analyzing loans. However, this outperformance decreases when the platform reduces the applicant's characteristics available to the investor.

[4] Hard information is such information that could be accurately quantified and efficiently transmitted.

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The article *Research on Risk Factors Identification of P2P Lending Platforms* (Lu and Zhang, 2018) complements subject-related literature with the analysis of P2P platform attributes (profitability, risk control, transparency, operation time, etc.) that can determine the probability of a platform being problematic. Data from 2259 P2P lending platforms were taken as a sample from binary logistic regression. It turned out that platforms with higher active operating time and average loan periods tend to be less problematic. The presence of fund custody (support of a third-party managed funds) secures the capital. Furthermore, companies that allow the transfer of creditors' rights and support automatic bidding tend to operate better. Meanwhile, the average interest rate negatively correlates with the platform's riskiness.

3.2. The Overview of Crowdfunding and Other P2P Financial Services

The term "crowdfunding" arose in the early 2006 as a part of a broader concept – crowdsourcing, a name coined by Jeff Howe earlier the same year.[5] Crowdsourcing may be defined as a practice of mobilizing the resources of a substantial number of people to solve specific problems in different areas voluntarily.

Crowdfunding represents a specific mechanism of fundraising, in which borrowers (capital seekers) may access a pool of capital through interacting with investors (capital givers) by means of a web-based crowdfunding intermediary (peer-to-peer platform). After the rapid technological development accompanied by rapid social media networks growth, capital seekers could easily approach a wide range of individuals interested in supporting innovative business initiatives and ideas. Crowdfunding serves as a general term to describe any type of web-based collective gathering of small contributions from a relatively large number of platform participants for further financing of a recipient (e.g., venture, project). A crowdfunding platform, which is often operated by a third party, manages arising transactions, provides payment facilities, and in some cases, carries out a fundamental analysis of a project before its introduction.

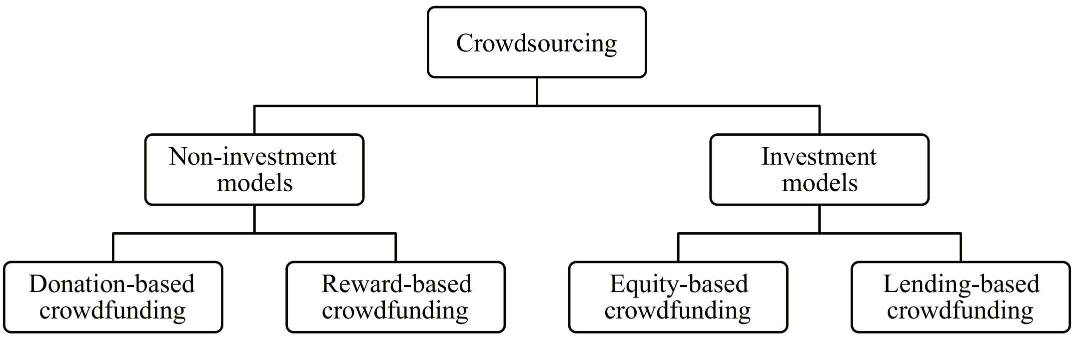
Different forms of crowdfunding may be distinguished by the type of remuneration the capital-givers receive (Lynn et al., 2018). Those types are as follows:

A. **Non-investment models**

B. **Investment models**

Figure 1

Breakdown of crowdsourcing by type of remuneration



Source: Lynn, Theo, John G. Mooney, Pierangelo Rosati, and Mark Cummins (2018). Disrupting Finance: FinTech and Strategy in the 21st Century. London: Palgrave Studies in Digital Business & Enabling Technologies.

[5] WIRED. 2006. The Rise of Crowdsourcing 2006. CNMN Collection.

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A. Non-investment models:

a. Donation-based crowdfunding implies that ventures are funded on a charitable or sponsorship basis and donor[6] has no anticipation of monetary or material return. In general, this type of crowdfunding is used to raise funds for projects not related to entrepreneurship. Experiment is an example of a donation-based platform. The platform serves for "All-Or-Nothing"[7] crowdfunding for scientific research projects.
b. Reward-based crowdfunding is similar to the donation-based one because the backer does not receive any financial remuneration, yet may expect a non-financial reward as a return for a contribution to a project. In this crowdfunding model, backers are driven not only by inherent or societal incentives and opportunity to be credited as funders but also by the possibility to receive merchandise ranging from small symbolic gifts to final products depending on the size of the pledge. Reward-based crowdfunding platforms may operate in either "All-Or-Nothing" or "Keep-It-All." Examples of such platforms are Kickstarter ("All-Or-Nothing) and GoFundMe ("Keep-It-All"). The indicator of total transaction value in the reward-based crowdfunding segment amounted to $6.9 billion in 2019 and is predicted to reach $12.0 billion by 2023 with the compound annual growth rate of 14.7% in 2019–2023 (Statista 2019).

B. Investment models:

Capital providers, involved in the mechanism of investment crowdfunding, may expect to receive some sort of remuneration in the form of financial return.

a. Equity-based crowdfunding (also: crowd investing): investors receive shares in a business, shares in profit generated by this business, and/or the voting power. This form of crowdfunding serves as an instrument for early-stage funding for young and innovative companies and may also help them to bridge the funding gap. The entire procedure may be broken into four steps. In the first step, the company submits its application, including the detailed plan, description, and other required information to the platform. The firm then undergoes a preliminary screening of its appropriateness to crowdfunding, the possibility of being deceitful, reputation, etc. Based on that, a subsequent decision is made on whether to place the business on a platform or to reject the application. The second step is uploading the presentative and investment-encouraging materials for potential shareholders. The third step is gathering the funds, and it continues within the timeframe specified by the platform (case of "All-Or-Nothing" model), funds are held at the escrow account within the funding window. After the deadline, money is transferred to the entrepreneurs provided that the funding target has been achieved; otherwise, funds are returned to the investors. The transaction value of the segment amounted to $4,794.9 million in 2019, with average values of funding $104,115 per application (Statista,2019).
b. Lending-based crowdfunding, the main target of this paper, is, similarly to equity-based crowdfunding, a commercial subtype of crowdfunding. The object of crowdlending is a debt agreement that contains the lender's credit claim to receive interest and redemption payments in the future. This type of crowdfunding is well-developed, holding a significant share of market volume in the industry of crowdfunding. The next section will examine lending-based crowdfunding in detail.

There are more peer-to-peer phenomena aside crowdfunding that are worth studying; however, they are less common. Foreign currency exchange platforms and invoice discounting (a.k.a. invoice trading) platforms that are based on the P2P concept are also interesting examples; however, they will not be studied in this research.

[6] According to the CROWD-FUND-PORT terminology, contributors in donation-based crowdfunding are referred as donors, in reward-based crowdfunding as backers, in equity-based crowdfunding as investors and in lending-based crowdfunding as lenders.

[7] Under "All-Or-Nothing" model, the project receives foundation only if the stated funding target is reached withing the prescribed timeframe (Bellefamme, Lambert & Schwienbacher, 2010).

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3.3. Model of Marketplace Lending and Critical Distinctions From Traditional Banking

The primary function of all platforms is generally the same – to serve as a two-sided intermediary and connect the borrower with the lender. Nonetheless, there might be differences in operating mechanisms. Apart from the traditional lending platforms (e.g., Zopa, LendingClub), other ones are launched with the aim to specialize and operate in particular industries, such as AgFunder, focused on the agri-food tech industry. A significant decrease in the number of intermediaries in the process of loan origination and the appliance of new practices to ease financial "frictions" such as information asymmetry and transactional costs considerably decreased the platform's charge on loan transactions. Moreover, several platforms do not charge anything for loan transactions.

There are several methods of categorizing marketplace lending platforms. Firstly, by application domain; companies may be divided into two groups: general platforms and professional platforms. (Wang et al., 2017) General platforms operate in a broad scope of individuals and small and medium-sized enterprises irrespective of loan purposes and intentions. The very first P2P lending platforms (i.e., Prosper and Zopa) originated as general types. Recently, various professional platforms focused on particular application areas have emerged. For example, previously mentioned AgFunder performs as an online venture platform for certified investors to finance agriculture and agricultural technology companies. Another example of a professional platform is LandlordInvest that specializes in supporting borrowers who are having difficulties with borrowing from traditional lenders due to an adverse credit event. The platform enables them to receive financing through buy-to-let mortgages and bridging loans. Although a great deal of marketplace lending platforms rely on unsecured borrowing, LandlordInvest is a representative platform of property-backed marketplace lending. Another form of differentiating between marketplace lending platforms is based on the type of trading rule. (Wang et al., 2017) There are two groups in this category: auction-based and fundraising (nonauction-based) platforms. On platforms operating under auction basis, the price (i.e., interest rate) is determined by the Dutch Auction Rule. A borrower is obliged to construct a loan requirement specification list, which, apart from the information on creditworthiness and other necessary data depending on the platform's regulations, includes the highest interest rate accepted, soliciting duration (i.e., the time interval during which the listing will be open for bids from investors) and the required amount funded.

Provided that the platform accepts the loan request, it is posted and is observable for lenders. If a lender is willing to fund this listing during its soliciting interval, a bid is created that reflects the amount of money to be financed, and the minimum interest rate accepted. If cumulative bid amount of a particular listing exceeds the required amount in its soliciting duration, competition among bids will occur based on the interest rate, i.e., bids with higher rates will be outbid, and the bids with lower rates will be accepted. After the soliciting duration, the final treading rate is the same for all investors whose bids succeeded in an auction and is defined as the maximum rate of all successful submissions. As in the "All-Or-Nothing" principle, if the listing fails to gather the stated amount funded withing the soliciting period, it is expired, and all bids made are canceled. Based on the foregoing process, investors may also analyze the probabilities of their bid winning the auction on the particular listing and the likelihood of this listing being fully funded withing the soliciting period when making an investment decision.

Due to the complexity of an auction, most platforms ended their auction process and changed the trading rule. For the sake of high quality customer service and trading efficiency, they decided to carry out a less sophisticated procedure – fundraising. Thereby, company Prosper ended its auction after five years of operating in 2010.[8] Fundraising may employ either a fixed ("All-Or-Nothing") or flexible ("Keep-It-All") principles of setting the funding target, which were discussed in the previous section.

[8] Renton, Peter. (2019). Prosper.com Ending Their Auction Process. December 16. Accessed December 27, 2019. https://www.lendacademy.com/prosper-com-ending-their-auction-process-dec-19th.

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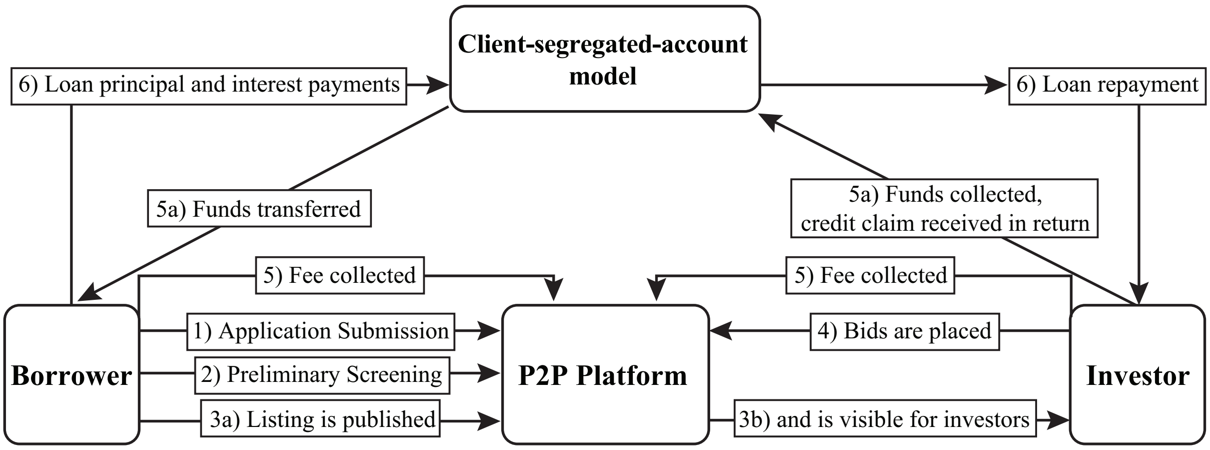
Figure 2
A process map of the client-segregated-account model



Source: Lenz, Rainer. (2016). Peer-to-Peer Lending: Opportunities and Risks. European Journal of Risk Regulation, pp. 688–700.

A general model may be described in chronologically ordered steps:

1. An individual or institutional borrower sends an application via the internet platform. The application consists of the amount requested and the maturity of the loan. Also, depending on the platform, the borrower is inquired to hand over additional information, such as borrowing history, credit certificates, debt to income ratio, employment length in years, amount of opened credit lines, etc.
2. After the application submission platform conducts a preliminary assessment of underlying credit risk based on the information provided and decides on whether the applicant matches the platform's risk categories. Some platforms assign a credit grade or score to reflect the riskiness. Finally, the platform offers the risk-appropriate interest rate to the borrower.
3. At this stage borrower may reject the proposal and exit the market. Otherwise, the application is listed on the platform for a defined soliciting duration. Individual loan listings are usually anonymized, while institutional ones are published with the borrower's title.
4. To become an investor, one needs to sign an agreement with the platform and complete the due diligence proceeding as a part of the Anti-Money Laundering Rules. Investors remain anonymous on the platform and assigned a coded username. During the soliciting period, investors may place their bids and observe the remaining amount required to match the funding target.
5. If a listing collects the funding target within the soliciting period, the loan money is obtained from the investors and is transferred to the borrower. Investors, in return, receive a document that writes down credit claims with the corresponding portion of the total loan principal and interest to be repaid by the borrower. Before that, the platform collects a fee from both parties: investors and borrowers. The critical point is the fact that the platform does not store the funds collected from investors. Transfers of funds are conducted simultaneously as counterclaims. (Lenz, 2016) There are three main loan origination models (Havrylchyk & Verdier, 2018):
   a. In the "client-segregated account" model, mostly exercised by the UK platforms, the platform itself originates the loan, but all the money flows through legally segregated client accounts. It is kept strictly separated from the platform's balance sheet. In the case of platform insolvency, creditors have no claim on the platform's client funds, and the contractual agreements of peer-to-peer loans remain valid.
   b. Opposite to the UK, the US and most European countries have different national banking regulations: origination of loans is allotted to licensed banks only. A "notary" model with credit institution (for the most part – commercial banks) involvement turns out to

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be obligatory for loan origination and payment service. After the borrower's application collects the funding target from investors on the platform, the loan package is hand to the partner bank, which originates the loan in the required amount. In 2–3 days, once the partner bank transfers funds to the borrower, the loan is sold to the marketplace company. At this point, the borrower's repayment obligation is transferred to the bank-affiliated marketplace company. The latter eventually issues notes to lenders, which reflect the corresponding share of funds that have been invested. The remaining steps mirror the "client-segregated account" model. The charge for White-Label-Banking intermediation depends on the volume of credit and ranges typically from 0.5% to 1%. As a rule, the identity of the partner bank is not revealed to the end-user.

c. In the "guaranteed-return" model, the platform acts similarly to the «client-segregated account" model and manages the investments of borrowers and repayments of lenders directly. However, a guaranteed return rate for borrowers is set by the platform. (CreditEase in China).

6. The last step is servicing the loan, collecting and dealing out interest and possible recovery payments up until the loan maturity date. Generally, marketplace loans are arranged in a form of monthly annuity loans. In the event of debtor's default, the platform is to arrange the collection of payments for account of crowd investors. Nevertheless, the platform is not legally responsible for possible losses carried by lenders. Some platforms practice sale of defaulted loans for the account of lenders to a debt-collecting agency for an agreed price in order to partially recover the credit claim. Others have developed automated litigation and recovery processes for defaulted credit lines. In the latter case, the recovery rates are higher.

As in traditional lending, the problem of information asymmetry may arise when the platform attempts to assess the borrower's creditworthiness. In the case of conventional banking, the assessment is mainly based on the analysis of systemized*,* implicit, hard information (i.e., financial statements, tax reports, etc.). Apart from this type of data, banks often possess non-codified information that was collected through an interview or obtained from previous credit history while dealing with a long-time customer. In P2P lending, the company is unable to acquire such information due to the lack of personal contact with a customer and the time scarcity devoted to deciding on the approval and level of the interest rate. A concept of big data comes into play instead. The structure of contemporary social media services inevitably leads to an individual's digital social footprint in the form of social media activities, preferences, age, education, social circle, etc. These data may effectively substitute the personal interviews and other conventional methods of forming the level of interpersonal trust and assigning a credit score. Companies use special software that is often based on machine learning to conduct credit scoring, pricing and to decide whether to accept or reject the borrower's loan request, autonomously and without the involvement of the platform's management. As already mentioned, if the proper software architecture is used, there is the negligible cost of assessing a marginal loan request. However, the target percentage of failures to predict the outcome has to be met.

Another substantial difference from traditional banking is the lack of credit risk presence on platforms' balance sheets. This fact relaxes the requirement for an equity loss-absorption buffer and the need for partial coverage of the originated loan with their equity capital. Thus, there is a lack of dependence between the value of queries and the equity requirement. Platform clients benefit from the lower cost of funds for borrowers and/or higher returns for the investor. The aggregate benefit equals the banks' interest margin, which is not charged in this case, less platform fees. In traditional banking, an institution obtains profit relying on interest margin between deposits held and loans provided. This does not apply to marketplace lending companies

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since they derive revenues from the transaction, servicing, loan origination, and other fees. Their profits, therefore, are directly unaffected by interest rate market fluctuations. Loan origination fees are deducted from the loan before transferring funds to a borrower. Origination fees vary across platforms and depend on the value of credit and type of borrowers, starting from 1% for large businesses and reaching 6% for SMEs. The servicing fees are calculated per annum based on the amount outstanding on any loan and are deducted from the loan repayments made by borrowers. Servicing fees vary less and are, on average, around 1%.[9] Companies are indeed interested in processing as many queries as possible since their revenue is partially subject to it. At the same time, an intermediary is motivated to act prudently and conduct adequate credit risk assessments since the platform's reputation and revenues are subject to the rate of return yielded for investors.

4. HYPOTHESIS AND PEER-TO-PEER LENDING MODEL

We verify the following research hypothesis: The method of credit scoring is applicable in alternative lending environment. Additionally, the quality of the final version of the logistic regression model and, thus, the scorecard, may be enhanced by more advanced variable pre-processing. In our case, variables binning based on selected indices (Weight of Evidence and Information Value) allowed to pre-select the most meaningful explanatory features. Investors select the preferred cut-off point subject to their risk acceptance level. To do so, they apply an expected profit/loss method, and based on the specificity and sensitivity values, choose the cut-off point subject to the highest expected profit.

In order to confirm or deny the above-mentioned hypothesis, the research which explores recent studies and open-source data on marketplace lending is done. The scorecard development is based on the P2P loans open data set that contains repayments record along with both hard and soft features of each loan. The quantitative part consists in applying a machine learning algorithm in building a credit scorecard, namely logistic regression. The objective is, through descriptive and quantitative analysis, to select the best features that allow for differentiating the loan performance in the marketplace lending environment and process the data, followed by scorecard construction and quality assessment.

4.1. Marketplace Lending From the Lender's and Borrower's Perspective

Investors may estimate the annual risk-adjusted returns received by subtracting the annual servicing fee and annualized bad debt loss from the gross profit (gross interest rate). Table 1 represents the annualized return less fees and bad debt losses by platform and year of loan origination. The values of net ROI varied significantly in 2015; however, the variance has decreased, accompanied by an increase in average return approaching 2020. These values, however, are applicable only in the case of a well-diversified portfolio containing a high number of loans. At this point, investors may benefit from diversification software instruments that may process automatic order placement depending on the preset amount invested per loan, risk grade, maturity, etc.

[9] Oxera Consulting LLP. (2016). The economics of peer-to-peer lending. Independent economic assessment, Oxford: Peer-to-Peer Finance Association.

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Table 1
Annualized return less fees and bad debt losses by platform and year of loan origination

Platform / Year	2015	2016	2017	2018	2019	2020
Lending Club (US, SME, PL*)	4.69%	4.31%	4.75%	4.81%	6.66%	N/A
Funding Circle US (US, SME)	2.6–2.8%	4.1–4.9%	5.3–6.2%	5–6.3%	5.7–7.8%	N/A
Rate Setter (US, PL)	4.8%	4.3%	4.0%	4.4%	4.4%	N/A
LendingCrowd (UK, SME)	6.92%	5.24%	5.53%	8.05%	7.94%	9.16%
MarketFinance (UK, SME)	2.88%	4.46%	4.83%	5.96%	6.39%	7.25%

* Personal loans.

Source: Funding Circle (2019), LendingClub (2019), RateSetter (2020), LendingCrowd (2020), MarketFinance (2020).

A comparison of these values with interest rates that are offered on deposit bank accounts shall also be avoided. The investments on the P2P lending market are, most of the time, unsecured, and the capital invested is fixed until the maturity date. In contrast, funds on the bank account (except time deposit account and other non-transaction accounts) may be withdrawn on demand and without a fee. Despite the existence of secondary marketplace lending market, there is no guarantee of exit without high expense as a result of a discount. Moreover, according to the EU Directive on Deposit Guarantee Schemes, deposits on bank accounts at EU banks are guaranteed by EU member states up to a level of €100,000 per person per bank.

The investment risk in a particular loan request may vary. A classical concept of risk-return tradeoff is applicable, similarly to the one present in the case of portfolio provided by a corporate bond investment fund that consists of corporate loans. The risk also depends on the type of loan, since some platforms host not only unsecured loans but also asset-backed ones (e.g., property-backed). The existing and properly managed buffer fund may considerably reduce the lender's risk burden and smoothen the investment result in case of a bad debt or recession.

A large number of platforms make their up-to-date statistics (including annualized returns, projected and historical bad debt rates, lifetime default rates, the volume of buffer fund, etc.) publicly available on their webpages. Investors may collect their portfolio performance for a given period. However, neither these indices nor techniques of their calculation are standardized. The industry lacks a framework of rules and regulations for clear, well-defined standards for performance evaluation. Likewise, disclosure standards for information about borrowers or platforms' credit assessment methods are yet to be defined. As a result, this may create an obstacle for an investor to compare platforms adequately and to decide which platform to select. The regulatory issue will be studied more broadly in the following chapter.

Borrowers benefit in terms of additional choice of loan options offered by marketplace lending, which are now broadly comparable to traditional banking solutions when it comes to the cost of borrowed funds. The emergence of marketplace lending brought an additional portion of the competition to the lending industry. As a result, SMEs may access funds from an additional source. That is, the share of funds borrowed by SMEs from traditional channels has fallen by more than a fifth in recent years. The Funding Circle in their survey of SME clients has noticed that the rise of popularity of alternative sources of finance is caused by shorter period from submitting application and loan pay-out (31% of customers) and simplicity of obtaining a loan (28% of customers).

P2P lending is accessible online at any time of the day; the number of documents and forms is rather low, which reduces bureaucracy. Other borrowers also notice the lack of collateral required for the majority of loan requests and the possibility of premature loan cancellation without a fee imposed. Borrowers with bad credit history and those unable to access banks benefit from an

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additional source of funding. 21% of Funding Circle customers report that they wouldn't be able to access the funds through a bank.[10] One may presume the presence of adverse selection: borrowers with low default risk will borrow from banks, and those with higher default risk will enter the marketplace lending. There is, however, no empirical evidence to prove that statement.

The major drawback of the model of P2P lending is that a potential borrower cannot be sure if they will get the required funds even if a platform accepts the application. Given the specific loan volume, interest rate, maturity, and credit grade, lenders may refuse to supply the needed amount of funds. To address this problem, platforms often raise the interest rate until the offer becomes sufficiently attractive. The next shortcoming of the marketplace model is that credit risk assessment lacks disclosure; borrowers are not aware of the data that the platform uses to analyze one's creditworthiness. This may bring a possible problem of discrimination into the industry based on gender, race, migration status, etc. The problem may be solved by introducing an appropriate legal framework.

5. RESEARCH OF METHOD OF SCORECARD CREDIT RISK ASSESSMENT

5.1. Concepts of Credit Scorecards and Linear Regression Machine Learning Algorithm

One of the most critical factors in investors' profitability and prosperity of their lending decisions is their ability to adequately measure credit risk involved in loan requests and borrower's creditworthiness in particular. One option is to refer to the subjective technique to estimate the probability of default (PD); alternatively, one may apply the objective approach to credit risk assessment – method of credit scoring. Credit scorecards are widely utilized by banks to distinguish "bad" clients from the "good" ones, since they may benefit from extensive client data collected from their experience or access databases of credit information bureaus.[11] Although a typical non-institutional marketplace lending investor has no access to such comprehensive data, this technique still may be of particular interest, since a platform discloses certain loan and borrower's features to investors. Among others, an investor may observe borrower's Debt-to-Income Ratio (DTI), the number of derogatory public records, total credit revolving balance, latest FICO Score[12] range, and many more. Also, listing-specific grade, interest rate assigned by platform itself as well as loan amount, and Equated Monthly Installment (EMI) are displayed. Thus, credit scorecards appear as quite an attractive objective technique for an investor to assess the creditworthiness of a particular loan request, since data are already provided.

There are some significant benefits of scorecards for credit assessment; for instance, it removes the possible bias which may arise when analyzing only good non-defaulted applications, thus minimizing the survivorship bias risk.[13] Given that credit scorecards are founded on fairly large data samples, they may include a wide range of features to extract the correlation between variables and bad loan performance. Despite the vast number of characteristics and observations, the algorithm's processing time is efficient, which minimizes process time and cost and produces fewer errors.

In the classical credit scoring approach, there are two types of scoring techniques: application and behavioral. The principal difference is that the application scorecard (AS) is created for

[10] Funding Circle. (2016). Small Business, Big Impact: The changing face of business finance. Evidence from Funding Circle, London: Centre for Economics and Business Research.

[11] An example of such credit bureau is Biuro Informacji Kredytowej S.A. (BIK) – an organization established by the Polish Bank Association and private banks, which gathers, processes and shares data on the credit history of banks', credit unions' customers and also some non-bank lending companies.

[12] FICO® score is one of the most well-known credit scores designed by the Fair Isaac Corporation.

[13] Survivorship Bias Risk is the risk that an investor's decision may be misguided when considering only "good" loan requests based on published return data.

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a specific lending company and a particular product (e.g., revolving loans, mortgage loans) and utilizes its historical data to evaluate at the application stage. They may include characteristics such as personal data, application data[14], and information provided by credit bureaus. On the contrary, behavioral scoring (B.S.) is predicated on based on time-dependent attributes of debtors and on how these attributes change once the loan contract is originated. They may take into consideration the borrower's credit behavior (credit limits, number of current credit lines, open bank accounts, deposit balance, granted credits, etc.). The general problem of credit scorecards is the lack of an explicit theory behind the chosen independent variables in classifying the loan outcome. There are, however, some papers that provide advice on variable selection. The general recommendation is to select interpretable variables based on discriminatory power, future availability, legal issues, etc.[15] The number of variables in scorecard should lie in between 8 and 15 to provide stability and keep relatively high predictive power even if the profile of one or two variables changes. Scorecards with an insufficient number of characteristics are more vulnerable to minor changes from the applicant's profile, making the scorecard unable to remain stable over time. Recent research confirms that there is no universal number of variables that should be included in scorecard development.

The idea of a credit scorecard is to choose such a cut-off score in which the final sum of scores for each attribute is present in the scorecard for a particular application. There are various techniques to determine specific scores and cut-off points. Generally, these methods are divided into parametric ones, where the number of parameters is finite and fixed with respect to data (e.g., linear regression), and non-parametric ones, where the potential number of parameters is independent of data and may potentially be infinite (e.g., decision trees, neural networks). This paper is going to focus on parametric statistical techniques, or more precisely – on logistic regression. The logistic regression algorithm is a regression analysis technique that belongs to generalized linear models (GLMs), designed to analyze the relationship between a dependent (explained) variable and one or more independent (explanatory) variables, in other words – regressors. This model has close ties with the classical linear regression model (CLRM); however, the latter is intended for continuous dependent variables only, meanwhile the logistic regression functions with binary and categorical variables with more than two levels. Depending on the form of dependent variable models are classified as: binary logistic regression – model with binary dependent variable; multinomial logistic regression – model with unordered categorical dependent variable with more than two levels; and ordinal logistic regression – model with ordered categorical dependent variable with more than two levels.

Binary logistic regression is a suitable instrument for credit scorecards development since the dependent variable is a good/bad flag that represents the loan outcome – bad meaning failure to pay and good – successful repayment. In contrast to CLRM, it calculates the conditional probability of dependent variable taking a specific value (0 or 1 if the dependent variable is coded as a binary variable) subject to the values of independent variables, for instance, in the case of one independent variable $p(X) = Pr(Y = 1/X)$, where Y is dependent, and X is independent variables. Parameters reflect the relationship between explained and explanatory variables, such that: $p(X) = \beta_0 + \beta_1 X$. Fitting a straight line would be inappropriate in case of a binary outcome; therefore the sigmoid-shaped function is used: $p(X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}}$; alternative form is $\frac{p(X)}{1 - p(X)} = e^{\beta_0 + \beta_1 X}$; where the left-hand side (LHS) of the equation is defined as odds ratio that ranges from 0 to $+\infty$, indicating low and high probabilities of event $p(X) = Pr(Y = 1/X)$ correspondingly. Taking the natural logarithm of both sides gives the logistic

[14] E.g. term, requested amount, EMI, purpose, joint or individual application, collateral, etc.

[15] Siddiqi, Naeem (2017). Intelligent Credit Scoring: Building and Implementing Better Credit Risk Scorecards. Hoboken: John Wiley & Sons.

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regression function (logit): $\ln\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X$. Similary to CLRM, a one-unit increase in X increases the value of LHS (logit) by β_0. The change in conditional probability, $p(X)$, depends on the value of an independent variable. For multiple independent variables: $p(X) = \frac{e^{X\beta}}{1+e^{X\beta}}$; where X is the matrix of independent variables, and β is the matrix of parameters.

The Maximum Likelihood Estimation (MLE) method is used to find the matrix of estimates for parameters β. The Likelihood Function takes the following form $L(\beta) = \prod_{i=1}^{n} p(x_i)^{y_i}(1-p(x_i))^{(1-y_i)}$. Once parameters are estimated, the probability that the dependent variable takes value 1 may be found for a specific combination of independent variables. For one unit increase in an independent variable x_k, the change in odds ratio is e^{β_k}.

5.2. Database and Features Description. Initial Data Cleaning and Processing

The main instrument of the quantitative part of research and modeling is an integrated development environment for R language – RStudio 1.2 combined with the smbinning package. The initial data set contains full Lending Club information on accepted loan applications for the period from 2007 up to the 3rd quarter of 2019 with 150 variables and 2 650 550 observations. Some variables require significant cleaning. Several characteristics are available only ex-post from the database; thus, they are not visible for an investor on the platform's website. Given that the aim is to construct a scorecard that will be useful in practical terms, one shall choose among variables that are available for an investor when deciding to lend money or to forgo a particular listing. Variables of interest were picked, provided that they are available on the platform website. The dependent variable is Loan Status, it is a categorical (factor) variable with eight levels, according to the LendingClub data dictionary:

– Charged Off – Loan for which there is no longer a reasonable expectation of further payments. Generally, Charge Off occurs no later than 30 days after the Default status is reached.
– Default – loan has not been current for 121 days or more.
– Fully Paid – loan has been fully repaid, either at the expiration of the 3- or 5-year term or as a result of a prepayment.
– Issued – a new loan that has been approved by LendingClub reviewers, received full funding, and has been issued.
– Current – loan is up to date on all outstanding payments.
– In Grace Period – loan is past due but within the 15-day grace period
– Late (16–30 days) – loan has not been current for 16 to 30 days.
– Late (31–120 days) – loan has not been current for 31 to 120 days.

The defaulted credit line is assigned default status once the payment is delayed for 121 days (i.e., for an extended time). The charged-off state is consecutively assigned to defaulted loan, and the remaining principal balance of the note is deducted from the investor's account balance. Thus, these statuses indicate the same practical loan outcome – default and differ in a formal principal deduction from an account. In this research, a bad loan outcome is recognized as either Charged Off or Default status of the credit line. The Fully Paid state is perceived as good loan outcome. Listings with other states are disregarded and removed.

Table 2 presents the description of the dependent variables that have been selected from the initial pool of features. After the variable selection and data cleaning, the approximate number of observations is more than 1.2 million. The handling of such large amount of data is resource-consuming. Therefore, after removing listings with missing information, 400 000 observations were randomly selected from this data set. An additional binary variable (good/bad flag) "DEF" was introduced with values 1 for bad loan outcome and 0 for good loan outcome.

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Table 2
Description of independent variables

Variable title in R	Description
total_acc	The total number of credit lines currently in the borrower's credit file. **Numerical variable.**
term	Loan duration. Values are in months and can be either 36 or 60. **Factor variable** with two levels: "36", "60".
revol_util	Revolving line utilization rate. **Numerical variable**.
revol_bal	Total credit revolving balance. **Numerical variable**.
pub_rec	Number of derogatory public records. **Numerical variable**.
home_ownership	Home ownership status provided by the borrower or obtained from the credit report. **Factor variable**. Levels*: "Rent", "Own", "Mortgage".
inq_last_6mths	The number of inquiries in past 6 months (excluding auto and mortgage). **Factor variable** with nine levels from "0" to "8".
open_acc	The number of open credit lines in the borrower's credit file. **Numerical variable**.
mort_acc	Number of mortgage accounts. **Numerical variable**.
loan_amnt	The listed amount of the loan applied for by the borrower in $ US **Numerical variable**.
avg_fico**	The average of upper and lower boundary range values the borrower's last FICO belongs to. **Numerical variable**.
int_rate	Interest Rate on the loan. **Numerical variable**.
installment	Equated Monthly Installment (EMI) in $ US **Numerical variable**.
grade	Loan grade assigned by LendingClub. **Factor variable**. Levels: "A", "B", "C", "D", "E", "F", "G".
emp_length	Employment length in years. **Factor variable**. Levels: 12 level from "< 1 year" to "10+ years".
dti	A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LendingClub loan, divided by the borrower's self-reported monthly income. **Numerical variable**.
delinq_2yrs	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years. **Numerical variable**.
annual_inc***	The self-reported annual income in $ US provided by the borrower during registration. **Numerical variable**.

* Initially, the variable contained the level "Other", which has been omitted.
** Generated as an arithmetic average of "last_fico_range_low" and "last_fico_range_high" variables.
*** Observations only with verified annual income are included in the final data set.

Source: LendingClub. (2018). "Data Dictionaries." LendingClub. Accessed March 28, 2020. www.help.lendingclub.com/hc/en-us/articles/216127307-Data-Dictionaries.

Table 3 presents the summary descriptive statistics: mean values, standard deviation, as well as minima and maxima values of each explanatory numeric variable. The first three variables in the table (i.e., annual income, revolving balance, and loan amount) have very high standard deviation values, standing out from the rest of features and generating quite a diverse data set with diverse applicants.

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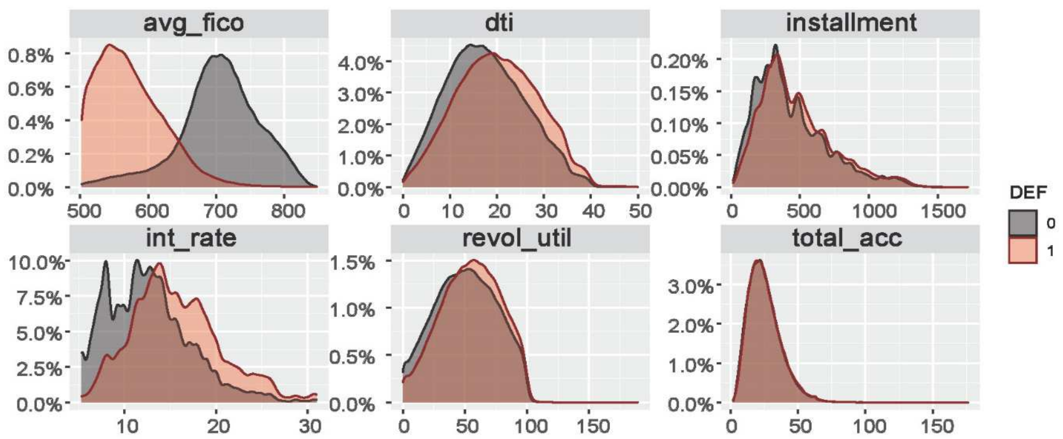
Table 3
Descriptive statistics for independent numeric variables

Variable	Mean	Std.Dev.	Min	Max
annual_inc	77568.86	71367.47	2500	9550000
revol_bal	16473.48	22523.11	0	2560703
loan_amnt	14454.94	8706.56	1000	40000
avg_fico	680.26	76.21	502	848
installment	439.58	261.33	14	1720
revol_util	51.50	24.46	0	189
total_acc	25.30	12.05	2	176
dti	18.18	8.38	0	50
int_rate	13.18	4.75	5	31
open_acc	11.74	5.52	1	84
mort_acc	1.68	2.01	0	37
delinq_2yrs	0.33	0.89	0	30
pub_rec	0.22	0.60	0	47
Obs.		400,000		

Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

Figure 3 consists of kernel density approximations for several continuous variables by loan outcome. Despite the generally positive (right) skewness tendency, most variables are approximately bell-shaped. At this step, conclusions about the data may already be drawn. Some variables have quite high (e.g., Average FICO and Interest Rate) and moderate (e.g., Debt-to-Income) discriminatory power. Whereas some variables (e.g., Total Number of Credit Lines) have negligible differences in distributions depending on loan outcome.

Figure 3
Kernel density estimations for selected numeric variables



Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

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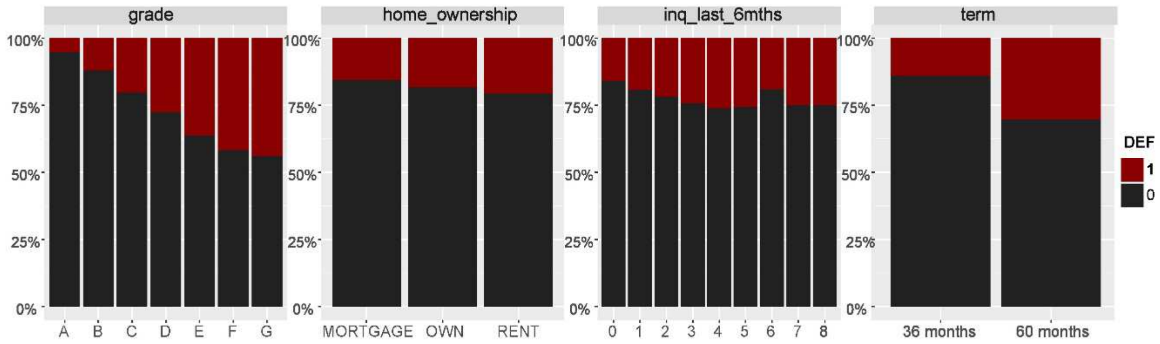
Figure 4 allows for graphical analysis of selected factor variables subject to the loan outcome. The situation is similar, the percentage of defaulted loans differs noticeably by grade and term. However, the relation is not that distinctive in case of home ownership and inquiries during the last 6 months.

Figure 4
Levels of factor variables by loan outcome



Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data

Moreover, the inquiries in the last 6 months are an ordinal factor variable, and the general relation in positive, the percentage of defaulted loans grows as the number of inquiries increases; however, there is an apparent nonlinearity in from of bad rate drop created by level "6".

5.3. Variables Pre-Processing. Fine and Coarse Classing

Since the scorecard development is based on logistic regression, explanatory variable transformations and addressing data issues are required. Rather than proceeding with an analysis of variables predictive power, solving problems of nonlinearities and outliers manually for each feature, this research suggests implementing an algorithmic method of variable transformation as the first step of variables pre-processing.

As a screening benchmark for pre-processing, this research employs the Fine Classing concept. It helps to reveal the structure of every single variable and its relationship with the dependent variable. Fine classing suggests that the variable is binned based on Weight of Evidence (WoE) and Information Value (IV) indices. This research uses the quantile approach, meaning that the number of bins is subject to the type of quantiles. More precisely, the decile method is applied through smbinning.custom function. As a result, the number of bins is always fixed and is equal to 10.

When it comes to the factor variables, at this point of initial pre-processing, factors are not changed. Weight of Evidence (WoE), a measure of the predictive power of the independent variable, discloses the relationship between dependent and explanatory variable and may be calculated for i-th bin as $\mathrm{WoE}_i = \ln\left(\frac{\%\text{ of non-defaults}_i}{\%\text{ of defaults}_i}\right)$.[16] As follows, the higher the relative share of non-defaults in a particular bin, the higher the WoE for that bin and, therefore, observations related to that bin are less prone to default.

[16] $\%\text{ of defaults}_i = \frac{\text{no. of defaults subject to bin}}{\text{total number of defaults}}$; $\%\text{ of non-defaults}_i = \frac{\text{no. of non-defaults subject to bin}_i}{\text{total number of non-defaults}}$.

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Table 4
Indices for univariate analysis

Variable	IV	GINI	Correlation
avg_fico	4.1023	0.8680	
grade	0.4555	0.3586	int_rate
int_rate	0.4398	0.3576	grade
term	0.1930	0.1984	
dti	0.0832	0.1639	
loan_amnt	0.0501	0.1248	installment
installment	0.0419	0.1059	loan_amnt
mort_acc	0.0277	0.0911	home_ownership
revol_util	0.0287	0.0900	
inq_last_6mths	0.0279	0.0847	
annual_inc	0.0206	0.0798	
home_ownership	0.0231	0.0792	mort_acc
open_acc	0.0119	0.0621	
emp_length	0.0112	0.0397	
revol_bal	0.0034	0.0326	
pub_rec	0.0056	0.0286	
delinq_2yrs	0.0041	0.0249	
total_acc	0.0016	0.0183	

Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

The next step is discriminatory power assessment of variables and univariate analysis by dint of: GINI index (G) – measure of discriminatory power, higher values indicate higher discriminatory power; Information Value (IV) – another distinguishing power index, higher values indicate higher predictive ability. To recognize collinearity, Kendall's Tau[17] is calculated. The summary of indices and correlation analysis for each transformed feature are represented in table 4. Variables for which the Kendall's Tau exceeds **0.5** are displayed in the last column pairwise. Variables with a GINI index lower than **0.9** or IV lower than **0.25** are considered as weak predictors and are omitted in further analysis. If two variables are highly correlated and both satisfy GINI and IV thresholds, then the one with lower GINI is omitted. Variables that meet the above conditions are: "avg_fico", "grade", "term", "dti", "loan_amount", "mort_acc" and "revol_util". Appendix 1 contains complete sets of fine classing algorithm output graphs with descriptions for the abovementioned variables.

The last phase of sample pre-processing is generating a test subsample used to build a scorecard and train subsample used for validation. Best practices suggest that in case of sufficiently large samples, the train subsample constitutes from 70% to 80% of initial data. (Siddiqi, 2017) To ensure the preservation of initial bad and good outcomes' proportions, sampling with stratification (proportional sampling) is used. After the data splitting, train sample contains 70% of observations, and the percentage of defaulted loans is equal to 18%.

[17] This coefficient is appropriate for the calculation of correlation between ranked (binned) data.

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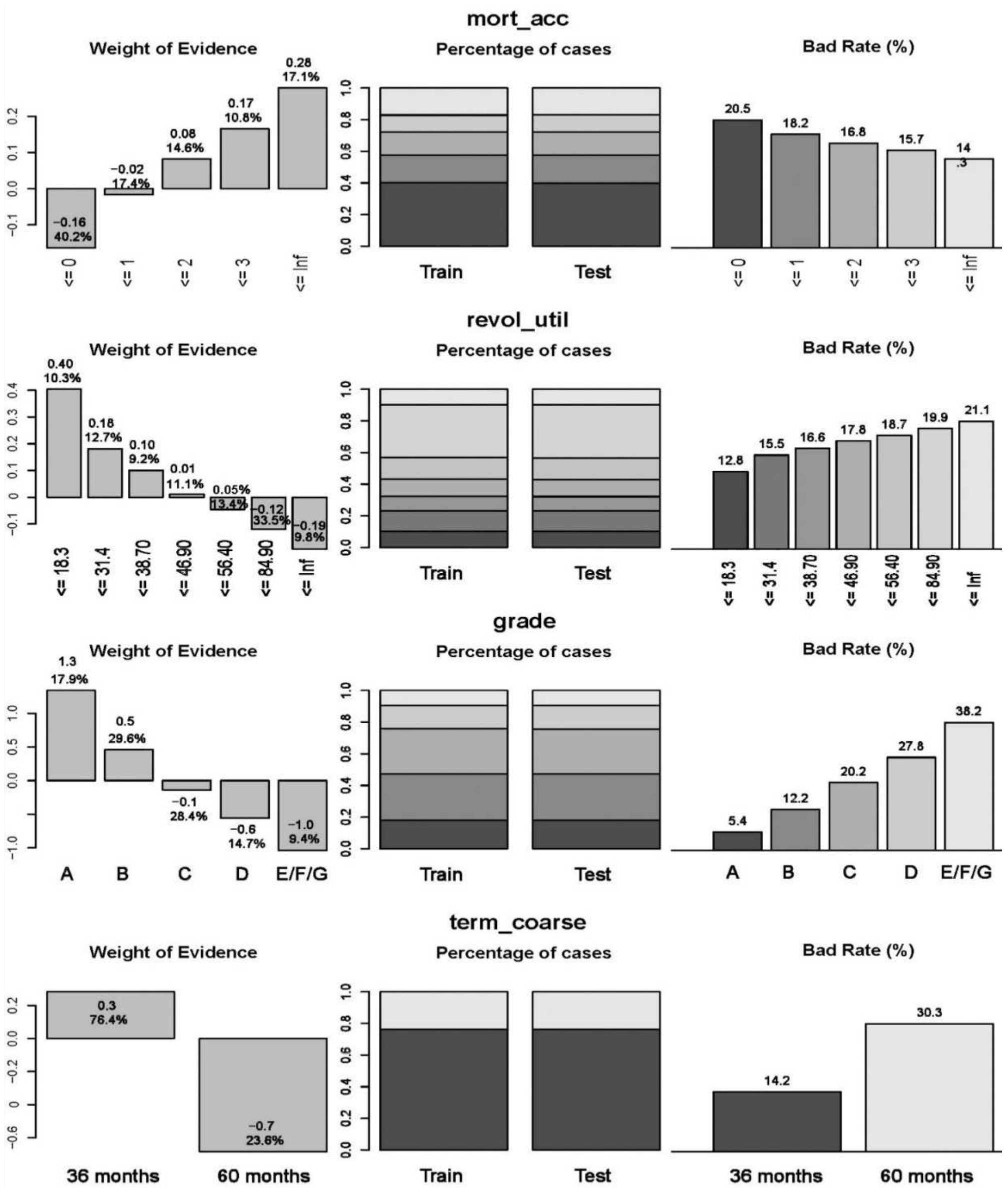
Bins generated by Fine Classing are not used in regression analysis. Coarse Classing is the following step to create more representative classes that will be used in modeling. Although Coarse Classing uses the same statistical measures, it is a more advanced technique. The smbinning package works in a tree-like method. Using the Conditional Inference Trees algorithm, it iteratively splits and then merges bins with similar WoE with respect to the dependent variable and maximizes the difference between classes, at the same time keeping the Information Value above the target level. The lower bound of IV is set at 0.1. Results of Coarse Classing of train sample for numeric variables are presented in Figures 5 and 6. Weight of Evidence diagrams give a picture of WoE values for each bin of specific variables (values on the top/bottom of each bar). Under these values, the share of observations contained for that specific bin in percentage is displayed.

Figure 5
Summary graphs of Coarse Classing, part I



Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

Percentage of cases bar plots can be used to compare the share of observation contained in each bin in train and test subsamples for each variable. Generally, it is preferred, that these values are approximately the same.

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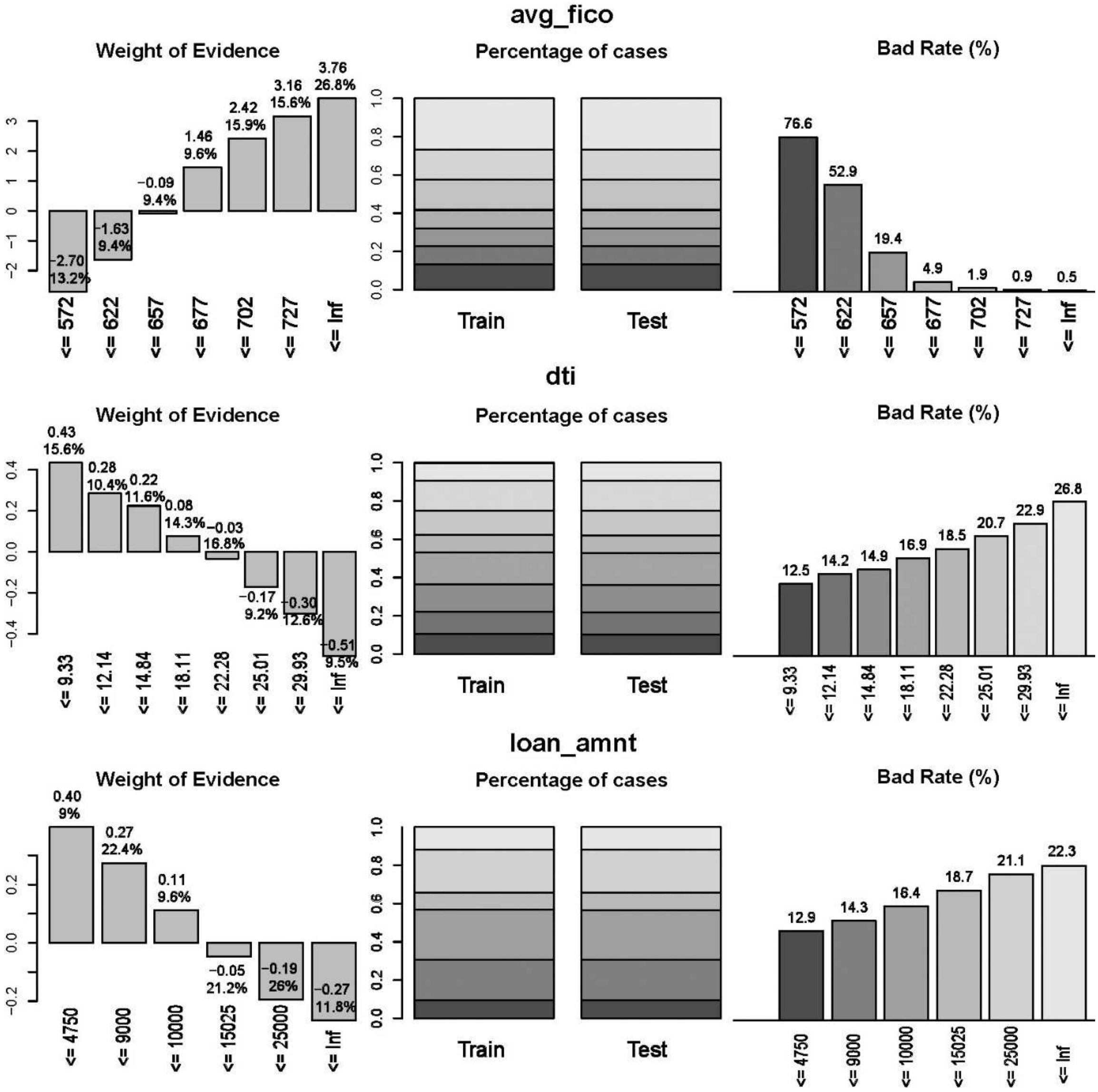
Figure 6
Summary graphs of Coarse Classing, part II



Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

The third graph in each set – Bad Rate (%), simply illustrates the percentage of defaulted loans in each bin of a specific variable. These sets of charts may be used to analyze the quality and adequateness of Coarse Classing. There are several details to be checked:

- each category (bin) should have at least 5% of the observations. Fine Classing indicated that variable *"grade"* has two underrepresented classes, namely "F" and "G". Since the WoE values of these classes were comparable and to prevent the overfitting, classes "E", "F" and "G" were merged into one level "E/F/G" with the cumulative percentage of 9.4%
- each category (bin) should be non-zero for both non-events and events. Neither Fine Classing nor Coarse Classing has shown that issue. Bad Rate is non-zero for all bins of each variable
- the WoE should be distinct for each category. Similar groups should be aggregated. Although, after Fine Classing, there were some bins with similar/same WoE, after Coarse Classing, this issue was eliminated
- the WoE should be monotonic, i.e., either growing or decreasing with the groupings. Fine Classing revealed the lack of monotonicity for variable *"loan_amnt"*. The problem was resolved by increasing the lower bound for each bin up to 9% in smbinning function.

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Since each point of the checklist is satisfied, the obtained discretization is appropriate. Initial independent variable values that are contained in the same bin are replaced with the WoE value of that particular bin for further logistic regression modeling. Thus, the amount of unique values for a variable is equal to the number of bins after Coarse Classing. Classifying with respected bounds and WoE values obtained from analyzing train sample are also substituted into the test sample. Nevertheless, these variables are treated as continuous in further modeling.

5.4. Modeling. Scorecard Development

Table 5 contains summary table of the final logistic regression model. Since initial values of variables are substituted with WoE, all estimates have to be negative, as a property of WoE transformation. Variable *"revol_util_woe"* has been excluded, since it has non-meaningful positive value of estimate. All variables are individually statistically significant according to the *Z*-value of Wald Test even at significance level as low as 0.01.

At the next step, based on the estimated model, fitted values (i.e., probabilities of default (P.D.)) and values of logit function are assigned to each observation for both train and test samples. Then, P.D.s are scaled to obtain scores. The following formula is used:

$$Score_i = PS - \frac{PTD}{\ln\left(\frac{1}{2}\right)} * \ln(ODDS) + \frac{PTD}{\ln\left(\frac{1}{2}\right)} * \ln\left(\widehat{ODDS}_\iota\right)$$

where:
PS – base number of points which corresponds to having ODDS value.
ODDS – value of odds, which is related to having PS score.
PTD – points to double, number of points that causes a double decrease in odds.

Table 5
Logistic Regression summary

Deviance Residuals				
Min	**1Q**	**Median**	**3Q**	**Max**
-2.3444	-0.2368	-0.1238	-0.0738	3.6317
Coefficients				
	Estimate	**Std. Error**	**Z-Value**	**P-Value**
(Intercept)	-1.5139	0.0087	-174.118	< 2E-16
avg_fico_woe	-1.0183	0.0044	-231.896	< 2E-17
dti_woe	-0.7582	0.0254	-29.804	< 2E-18
loan_amnt_woe	-1.2907	0.0374	-34.483	< 2E-19
mort_acc_woe	-0.3002	0.0464	-6.475	9.50E-11
grade_woe	-0.0539	0.0128	-4.220	2.44E-05
term_woe	-0.8915	0.0206	-43.208	< 2E-16
Null deviance: 264060 on 279994 degrees of freedom				
Residual deviance: 123187 on 279988 degrees of freedom				
AIC: 123201				

Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

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The final form of the transformation formula:

$$Score_i = 660 - \frac{40}{\ln\left(\frac{1}{2}\right)} * \ln\left(\frac{1}{72}\right) + \frac{40}{\ln\left(\frac{1}{2}\right)} * \ln\left(\widehat{ODDS}_i\right)$$

Table 6 summarizes results of model quality assessment. The p-value of L.R. test is 0, thus, the null hypothesis about joint insignificance of variables is rejected. P-value of Osuis-Rojek goodness-of-fit test does not allow to accept the null which states that the model is well fitted to data. Hosmer-Lemeshow show p-value equal to 0, which a well does not allow to accept the null about wellness of fit. However, p-value of Pearson's goodness-of-fit test is 1, thus the hypothesis that the model fits the data well is not rejected. ROC curves from model with intercept only and final model are compared by DeLong's test. P-value of the test is 0, thus, the null hypothesis stating that ROC curves from both models are equally good is rejected. Values of Kolmogorov – Smirnov test statistics from both test and train samples are quite high (> 0.77), indicating that distributions of scores for defaulted and non-defaulted clients in both test and train samples differ significantly, which is a good indicator. Population Stability Index (PSI) takes value lower than 0.1 (common rule of thumb), indicating that the model is stable. P-value of Komogorov-Smirnov stability test also does not allow to reject the null, which states that data from two periods (test and train) come from the same distribution, i.e., the model is stable. GINI values for test and trains samples are presented along with 95% confidence intervals. Indicators takes quite high values, 0.8881 and 0.8891 for train and test samples respectively, meanwhile 95% confidence intervals for these values are rather narrow.

Table 6
Logistic Regression quality assessment summary

LR	**Osius-Rojek**	**Hosmer-Lemeshow**	**Pearson's Test**	**ROC Comparison**
0	0	0	1	0
K-S Statistic Train	**K-S Statistic Test**	**Population Stability Index**		**K-S Stability**
0.7793	0.7779	0.0003		0.9171
GINI Train = 0.8881		**GINI Train 95% CI: [0.8860; 0.8902]**		
GINI Test = 0.8891		**GINI Test 95% CI: [0.8859; 0.8922]**		

Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

Although two of three goodness-of-fit tests are rejected, one shall not rely on p-values only when operating with large samples, since p-values of test in such sample quickly go to zero. Moreover, goodness-of-fit tests are not assessing the predictive ability of the model, but rather check for deviations of functional S-shaped curve.

The area under the ROC curve (AUROC) presented in Figure 7 indicates quite a high distinguishing capability of binary classifier. The percentage of AUROC is around 94.4%. Histogram of assigned scores by loan outcome based on the train sample is pictured in Figure 8. Green and red-colored shares of histogram bins represent non-defaulted and defaulted cases, respectively. The distribution is left-skewed: the mean value of the score is shifted leftwards. This is explained by the prevalence of non-defaulted cases in the train sample, which tends to have higher scores.

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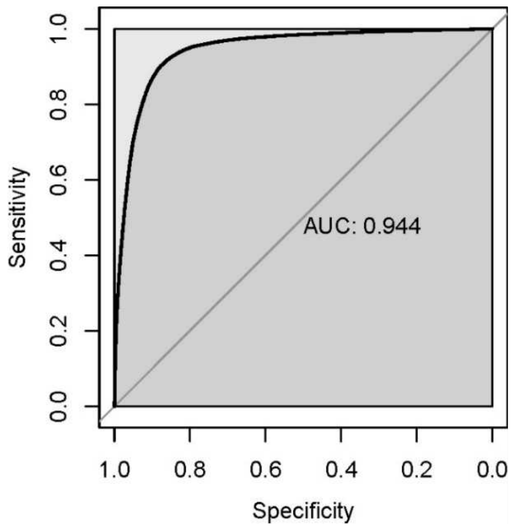
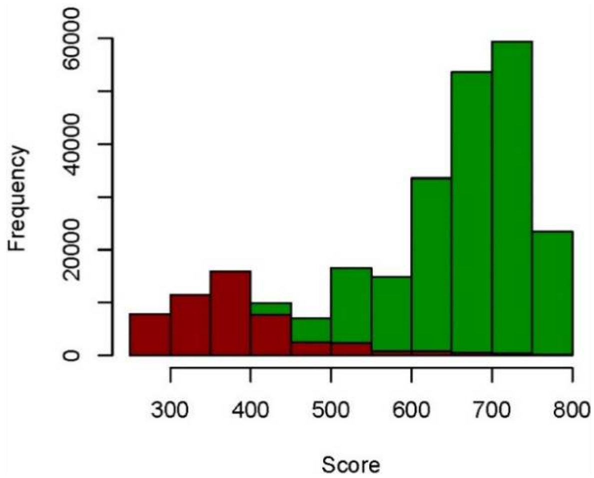
Figure 7
Receiver operating characteristic (ROC) curve in specificity and sensitivity space



Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

Figure 8
Histogram of scores by loan outcome



Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

The number of scores subject to each variable level is assigned by the following method:

$$points_{i,j} = \frac{\widehat{B}_J * \mathrm{WoE}_{i,j} * PTD}{\ln(0.5)}\ ;\ points_{intercept} = \frac{\ln\left(\frac{1}{e^{B_{intercept}}}\right) + \ln(ODDS) + \frac{\ln(2) * PS}{PTD}}{\ln(2)/PTD}$$

where:
$points_{i,j}$ – points subject to i-th level of j-th variable,
$\widehat{B}_J$ – an estimate of j-th feature.
$\mathrm{WoE}_{i,j}$ – WoE of i-th level of j-th variable.
$points_i$ – points subject to constant (initial score).
$B_{intercept}$ – value of intercept.

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The final scorecard is presented in Table 7. An amount of points that correspond to the specific level/interval of a variable is displayed in columns "Points". The base number of points is 500.57.

Table 7
Scorecard summary

Variable	Level	Points	Variable	Level	Points
Intercept	N/A	500.57	grade	E/F/G	-3.22
avg_fico	[0; 572]	-158.87	grade	D	-1.74
avg_fico	(572; 622]	-95.84	grade	C	-0.44
avg_fico	(622; 657]	-5.54	grade	B	1.43
avg_fico	(657; 677]	85.66	grade	A	4.16
avg_fico	(677; 702]	142.24	loan_amnt	(+ ∞; 25000)	-19.78
avg_fico	(702; 727]	185.98	loan_amnt	[25000; 15025)	-14.45
avg_fico	(727; + ∞)	221.01	loan_amnt	[15025; 10000)	-3.49
dti	[0; 9.33]	19.00	loan_amnt	[10000; 9000)	8.29
dti	(9.33; 12.14]	12.46	loan_amnt	[9000; 4750)	20.39
dti	(12.14; 14.84]	9.81	loan_amnt	(0; 4750]	29.59
dti	(14.84; 18.11]	3.32	mort_acc	0	-2.83
dti	(18.11; 22.28]	-1.48	mort_acc	1	-0.28
dti	(22.28; 25.01]	-7.54	mort_acc	2	1.42
dti	(25.01; 29.93]	-13.22	mort_acc	3	2.87
dti	(29.93; + ∞)	-22.24	mort_acc	(3; + ∞]	4.82
			term	60 months	-35.20
			term	36 months	14.55

Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

The last step in scorecard development is finding an optimal cut-off score, which will be referred to when making an investment decision. There are several approaches. One of them is to maximize the portfolio performance based on the expected profit and expected loss from a good and bad client, respectively. Another approach is to set the target acceptance or default rate of the portfolio. However, the above practices are subject to expected profits and losses specific to good and bad loan outcomes. This paper, thus, focuses on the comparison of cutoff point calculations based on Diagnostic Accuracy Indices (DAI) that are constructed from True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) value (e.g., specificity, sensitivity). Where Negative outcome (0) stands for non-default and Positive (1) outcome is defaulted loan. Analyzed approaches are:

– minimization of the *Sum of misclassification costs* = *FN* + *FP*; i.e., the sum of False Bad (type I error) and False Good (type II error) clients
– minimization of the p-value (maximization of a statistic) of a chi-squared test on the confusion matrix, achieving maximum discrimination power
– *Youden index* = (*Sensitivity* + *Specificity* – 1) maximization
– cut off score subject to the point, such that the distance to (0,1) point on ROC in False Positive and True Positive space is minimized

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– maximizing $F1\,Score = \frac{2 * TP}{2 * TP + FP + FN}$

– maximizing $Cohen's\ Kappa = \frac{Accuracy - P_e}{1 - P_e}$[18]

– maximizing $Matthews\ Correlation\ Coefficient\ (MCC) =$

$$= \frac{TP * TN - FP * FN}{Sqrt\left(\left(TP + FP\right) * \left(TP + FN\right) * \left(TN + FP\right) * \left(TN + FN\right)\right)}.$$

For each method, values of cut-off points are calculated based on a train sample. Afterwards, each cut-off point is applied to the test sample and measures for classifier evaluation are calculated.

Table 8
Cut-off points metrics

Metric	Cut-off Point	Accuracy	Sensitivity	Specificity
Misspecification Cost	415.4483	0.9063	0.7463	0.9414
Cohen's Kappa	432.8462	0.9036	0.8028	0.9257
ROC (0,1)	445.0417	0.8999	0.8412	0.9128
MCC	447.3703	0.8991	0.8470	0.9106
Youden Index	499.6972	0.8819	0.9017	0.8775
F1 Score	500.6436	0.8814	0.9026	0.8767
P-value	586.0022	0.8039	0.9577	0.7701

Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

Summary of cut-off points obtained from each approach are presented in Table 8. Methods are sorted by accuracy. ROC point and MCC approaches also are of similar accuracy; however, in this case, their Specificity and Sensitivity metrics are also comparable. They both offer higher Sensitivity, thus, accepting more loan applications, but at the cost of the greater share of False Negative rate. Cut-off points calculated based on the Youden Index and F1 Score metrics are of a virtually equal cut-off score. The P-value approach has the lowest accuracy. Misspecification cost minimization and Cohen's Kappa metric maximization are two methodologies that give the highest value of accuracy (i.e., the sum of correctly predicted outcomes as a share of the total number of applications). The difference in accuracy is negligible. There is, however, a noticeable tradeoff between sensitivity and specificity. The misspecification cost has higher specificity – an advantage in detecting True Negative outcomes; meanwhile, the share of correctly predicted Positive outcomes is higher in Cohen's Kappa approach.

18 $P_e = \frac{(TP + FP) * (TP + FN) + (TN + FP) * (TN + FN)}{(TP + TN + FP + FN)^2}$

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6. CONCLUSIONS

The aim of our research was to explore the phenomenon of peer-to-peer lending market model. In our paper a comprehensive view on the historical development of peer-to-peer lending in the financial environment, as well as the overview of the current situation on the alternative finance markets was presented.

Marketplace lending shows itself as one of the most promising and rapidly emerging forms of crowdfunding. It has developed enormously in recent years, providing more and more funding and investment opportunities for individuals and institutions. Among others, this form of crowdfunding is regarded as a potential competitor to traditional banking lending. The regulation of marketplace lending experienced a time lag; however, some countries with developed P2P lending industry have recently responded to the growing demand for adequate and industry-specific regulations with brand-new legal solutions.

The research hypothesis that the method of credit scoring is applicable in alternative lending environment is confirmed. The research has shown that scorecard derived from the logistic regression is a robust risk assessment instrument that can be used not only in the traditional financial environment but also in alternative lending, where both historical data and application-specific data are available.

Moreover, the research has shown that logistic regression approach to scorecard development provides high AUROC values, as well as sensitivity and specificity statistics that are comparable to more advanced machine learning models, provided that cut-off point is defined properly. Additionally, it was shown that quality of the final version of the logistic regression model and, thus, the scorecard, may be enhanced by more advanced variable pre-processing. In our case, variables binning based on Weight of Evidence (WoE) and Information Value (IV) indices allowed to pre-select the most meaningful explanatory features. The issue of choosing the appropriate cut-off point metrics was also addressed. Despite the fact that there might not be a huge absolute difference in accuracy, evidently, there is a clear trade off tendency between sensitivity and specificity for a given level of precision. Thus, investors should select the preferred cut-off point according to their risk acceptance level. Therefore, the latter two methods are the only ones that are similar in terms of accuracy, nonetheless with the apparent disparity in cut-off scores. One may try to apply an expected profit/loss method, and based on the specificity and sensitivity values, choose the cut-off point according to the highest expected profit.

The recent COVID-19 pandemic caused by SARS-CoV-2 virus has brought a noticeable disturbance to the financial market, particularly its lending division. The operational side of online platforms remained virtually unaffected, and employees continued their work remotely. Nevertheless, P2P lending platforms have faced a kind of "bank run". A particular group of investors who were alarmed by the previous crises want to retract their funds from platforms, regardless of the potential decrease in returns. Others actively use secondary markets to sell their investments with discounts. Some platforms, in turn, introduce withdrawal restrictions and increase the withdrawal processing time, since they are unable to service these outflows simultaneously. Although platforms are not directly affected by the increased number of defaults (investors bear this risk), they still finance their costs from the loan origination fees. The amount of originated loans has decreased, triggering platforms' liquidity issues.

On the contrary, many SMEs were in search of new funding solutions to resolve their liquidity issues. Thus, there may be a disparity of demand and supply of loanable funds on platforms. Government support aimed at SMEs may bring some relief to the market, as may deferred repayment solutions introduced by platforms for SMEs that are experiencing liquidity issues.

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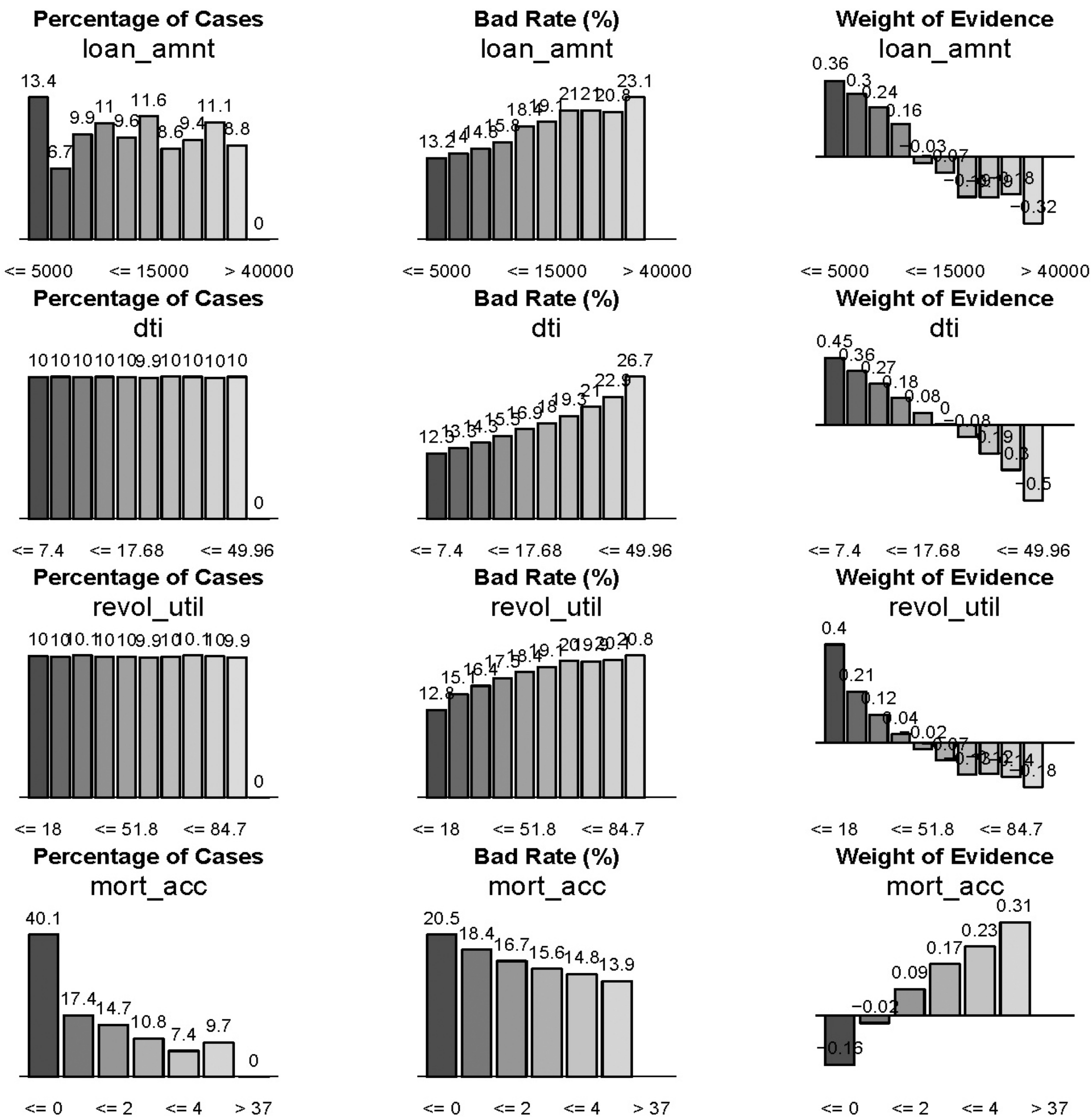
APPENDIX

Appendix 1. Summary of Fine Classing and Kendall's Tau analyses

Figure 9 contains sets of 3 graphs for each variable that were picked out as a result of variable quality assessment. The percentage of cases indicates the proportion of observations that falls into the specific bin. Bad Rate illustrates the percentage of defaults (G/B flag = 1) for a particular bin. Weight of Evidence displays calculated WoE for each bin.

Figure 9
Summary graphs of fine classing, part I



Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

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Figure 10
Summary graphs of fine classing, part II

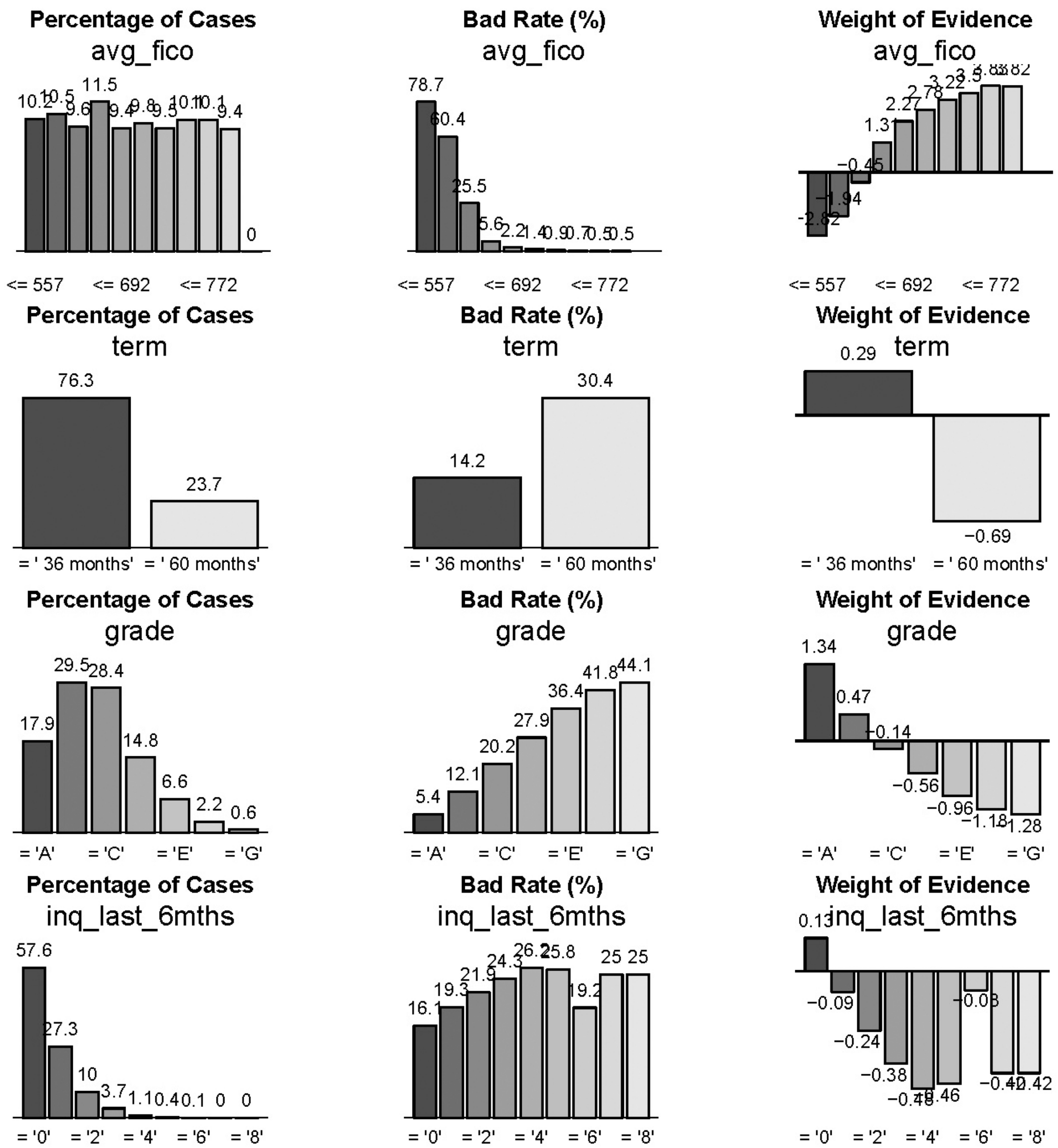

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Table 9
Kendall's Tau rank correlation coefficients

	loan_amnt	int_rate	installment	dti	revol_util
loan_amnt	1				
int_rate	0.0809	1			
installment	**0.7788**	0.0925	1		
dti	0.0277	0.1317	0.0313	1	
revol_util	0.0911	0.1908	0.1037	0.1256	1
mort_acc	-0.1623	0.0732	-0.1372	0.0246	-0.0228
avg_fico	-0.0332	0.2649	-0.0217	0.0738	0.1306
term_	0.3439	0.3376	0.1955	0.0592	0.0558
grade	0.0855	**0.8836**	0.0934	0.1438	0.1928
home_ownership	-0.1343	0.0611	-0.112	-0.0041	-0.0189

	mort_acc	avg_fico	term	grade	home_ownership
mort_acc	1				
avg_fico	0.0822	1			
term_	-0.1031	0.0694	1		
grade	0.0761	0.2817	0.3610	1	
home_ownership	**0.5287**	0.0728	-0.0967	0.0649	1

Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data

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