University of Warsaw
Faculty of Economic Sciences

Working Papers
No. 4/2021 (352)

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

Aleksy Klimowicz
Krzysztof Spirzewski

Warsaw 2021

WORKING PAPERS 4/2021 (352)

UNIVERSITY OF WARSAW
FACULTY OF ECONOMIC SCIENCES
WORKING PAPERS

Concept of peer-to-peer lending and application of machine learning in credit scoring

Aleksy Klimowicz, Krzysztof Spirzewski

University of Warsaw, Faculty of Economic Sciences

Corresponding authors: aleksy.klimowicz@gmail.com, kspirzewski@wne.uw.edu.pl

Abstract: Numerous applications of AI are found in the banking sector. Starting from front-office, enhancing customer recognition and personalized services, continuing in middle-office with automated fraud-detection systems, ending with 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 of applying a machine learning algorithm in building a credit scorecard, namely logistic regression.

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

JEL codes: G21, C25

1. Introduction

The recent explosive growth of brand-new alternative financial possibilities has brought about a lot of discussions and studies. One of them 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 affect a particular industry. Considerable changes have already occurred in lodging, file sharing, multimedia, etc. A decentralized network of credit relations more and more 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, 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 cutoff 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 dataset that contains repayments record along with both hard and soft features of each loan. The quantitative part consists of 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.

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 of the European Union as well as in the United Kingdom are performed. 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 modeling. 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 intricated the 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 storage 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 - 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. Abovementioned relations foster the 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 a need for the central intermediary involved. It first originated to describe such 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 2000's sequence of information technology innovations 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 adoption made the colossal impact of P2P in 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 performs as an instrument 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), and so further. Similarly, technological progress opened new horizons and opportunities for the financial sector by smoothening out the distance and access obstacles, 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.

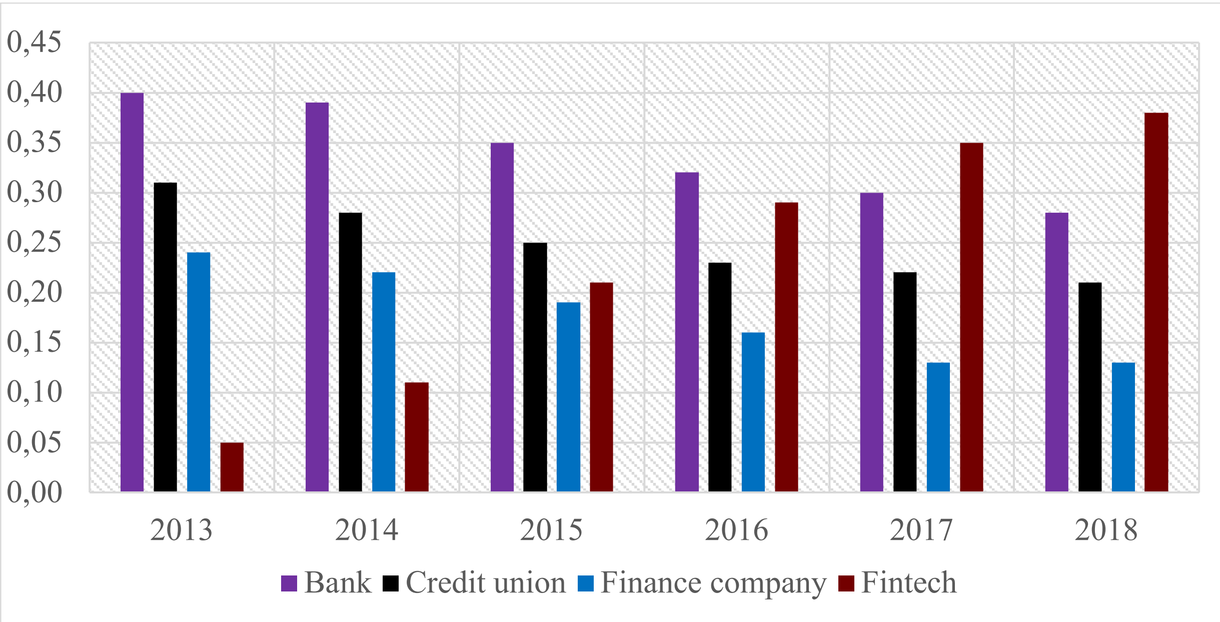
Initially, the P2P lending market consisted of individual investors and small businesses. Over time large firms and investors entered the market, and the term "P2P lending" became less descriptive, and the new name – marketplace lending came into use. There are some misunderstandings connected with these two terms. However, they are mostly the alternative expressions 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, it is primarily individuals and small businesses who are engaged in the lending cycle, when it comes to the marketplace lending - institutional investors enter the market. At the moment, the marketplace lending market may be broken up into consumer lending, business lending, and property lending. Consumer lending constitutes a significant part of marketplace lending and are granted for a variety of purposes, including debt consolidation, credit card refinancing, home improvements, and major purchases. Business lending is actively utilized by manufacturing, engineering companies as well as businesses operating in transport and utilities. Property lending firms provide services and products flexible financing models starting from bridging finance to commercial and residential mortgages, and construction and development investment opportunities. The very first P2P lending platforms - Zopa originated in the U.K. in 2005[1] and Prosper in the U.S. in 2006. 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 U.K. market of around 28,79%.[2] Throughout the 14 years of operating, the number of personal loans lent exceeded £4.8 billion for over 470,000 UK consumers, and the value of interest generated

[1] United Kingdom: BBC. 2005. Q&A: Online lending exchange.
[2] P2PMarketData. 2019. Accessed October 31, 2019. https://www.p2pmarketdata.com

surpassed £280 million for over 60,000 active investors.[3] The Prosper platform since 2006 lent more than $16 billion to over 980,000 consumers.

Throughout the years, the value of loans, together with the number of firms, drastically increased. In 2019 global transaction value of bank-independent loans for SMEs and for consumer loans via marketplace lending platforms amounted to around $267 billion; the number of successfully funded loans in that year was 66 million. It is forecasted that the global transaction value will be over $390.6 billion with a compound annual growth rate in 2019-2023 of 10%, and a number of successfully funded loans will reach 87.3 million in 2023.[4] Fintech and marketplace lending, as a part of it, has been confidently increasing its share in consumer and small business lending markets during the last decade, representing a direct competitor for traditional financial lending.

Figure 1. Share of personal loans granted in the U.S. from 2013 to 2018, by source



Source: Statista. 2019. Alternative Lending. September. Accessed December 12, 2019. https://www.statista.com.

Figure 1 depicts the data on personal loans from 2013 to 2018. Banks' market share during this period was decreasing from year to year. In contrast, the percentage of fintech was rapidly growing, starting from 5% of the total share in 2013 to more than 35% of personal loan volume in 2018 provided by fintech companies.

On account of low-cost information technology platforms are capable of gathering

[3] Zopa Bank Limited. 2019. Zopa.com. Accessed December 7, 2019. https://www.zopa.com
[4] Statista. 2019. Alternative Lending. Accessed December 12, 2019. https://www.statista.com.

a homogeneous array of information from each borrower on a widespread. Investors, consisting of sophisticated or unsophisticated and individual or institutional, entirely bear bad debt risk and conduct an additional borrower screening. This procedure of interaction between investor and platform leads to the joint making of information. This process initiates challenge with traditional banks which serve as exclusive information producer on behalf of investors.

It is, however, of fundamental importance to take into account that different government regulations apply for P2P platforms than for banks. Generally, fewer regulatory requirements allow for broader operational scope at the lower costs, at the same time, potentially generating additional risk.

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 hypothesis stating that the credit grade assigned by a platform reduces information asymmetry was not rejected in the analysis of 143,654 matured P2P loans funded in 2012 – 2013 *"Determinants of Loan Performance in P2P Lending"* (Möllenkamp 2017) performing as prevalent determining factor of bad debt, lower credit grade probability of bad debt increases. Factors that are positively correlated with high loan performance were 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. Paper *"Determinants of Default in P2P Lending"* (Serrano-Cinca et al. 2015) studied the determining factors within each credit grade. Similar to 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 found as efficient predictors for each grade class. Whereas 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[5] (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 rather than credit grades, since the latter may not accurately serve as estimates of

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

debtors' creditworthiness.

An empirical investigation of a large sample of PRC's P2P platform containing data on repayment records in working paper "*Adverse selection and credit certificates: evidence from a P2P platform"* (Hu et al. 2019) has shown that borrowers more attract lenders with high-grade certificates. Certificates are a technique of signaling in 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 platform's service quality and protection have significant impacts on the lender's trust in that 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 less sophisticated investors. 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.

The article "Research on Risk Factors Identification of P2P Lending Platforms" (Lu and Zhang 2018) complements the literature with analysis 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 was found out that platforms with higher active operating time and average loan periods tend to be less problematic. The presence of fund custody (support of third-party managed funds) creates protection for the security of capital. Furthermore, companies that allow creditors rights transfer and support automatic bidding tend to operate better. Meanwhile, the average interest rate negatively correlates with the platform's riskiness.

2.2. The overview of crowdfunding and other P2P financial services

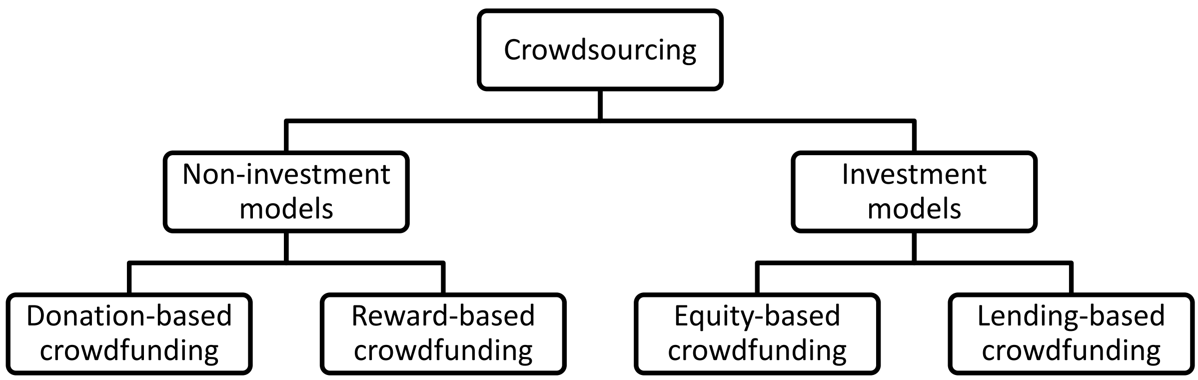
The term crowdfunding arose early in 2006 as a part of a broader concept – crowdsourcing, which, in turn, was initially coined by Jeff Howe earlier in the same year.[6] Crowdsourcing may be defined as a practice of mobilizing the resources of a substantial number of people to solve specific problems 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 way of a web-based crowdfunding intermediary (peer-to-peer platform). Following the rapid development of technology accompanied by rapid social media networks growth, it turned out to be much easier for capital seekers to 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 in advance of presenting it.

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 2. Break down 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.

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

A. Non-investment models:

a. Donation-based crowdfunding implies that ventures are funded on a charitable or sponsorship basis and donor[7] 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. An example of a donation-based platform is Experiment. The platform serves for "All-Or-Nothing"[8] crowdfunding for science-based research projects.

b. Reward-based crowdfunding is similar to the donation-based since backer does not receive any financial remuneration, nonetheless, anticipates in the majority of cases a non-financial reward as a return for a contribution to a project. In contrast to the aforementioned crowdfunding model, in this scenario, backers are driven not only by inherent or societal incentives and opportunity to be credited as funders but also by an ability 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 amounts to $6.9 billion in 2019 and is predicted to reach $12.0 billion by 2023 with the compound annual growth rate in 2019-2023 period of 14.7% (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 for young and innovative companies as an instrument for early-stage funding and bridging the funding gap. The entire procedure may be broken into four steps. In the first step, the business submits its application,

---

[7] 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.

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

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 of 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 withing the specified timeframe by the platform (case of "All-Or-Nothing model), funds are held at the escrow account withing the funding window. After the deadline, in case of successfully achieved funding target, money is transferred to the entrepreneurs; otherwise, funds are returned to the investors. The transaction value of the segment amounts to $4,794.9 million in 2019, with average values of funding per application of $104,115. (Statista 2019)

b. Lending-based crowdfunding, the main target of this paper, is, as well as 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 few 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, for instance, are also exciting topics for discussion; however, they will not be studied in this research.

2.3. Model of marketplace lending and critical distinctions from traditional banking

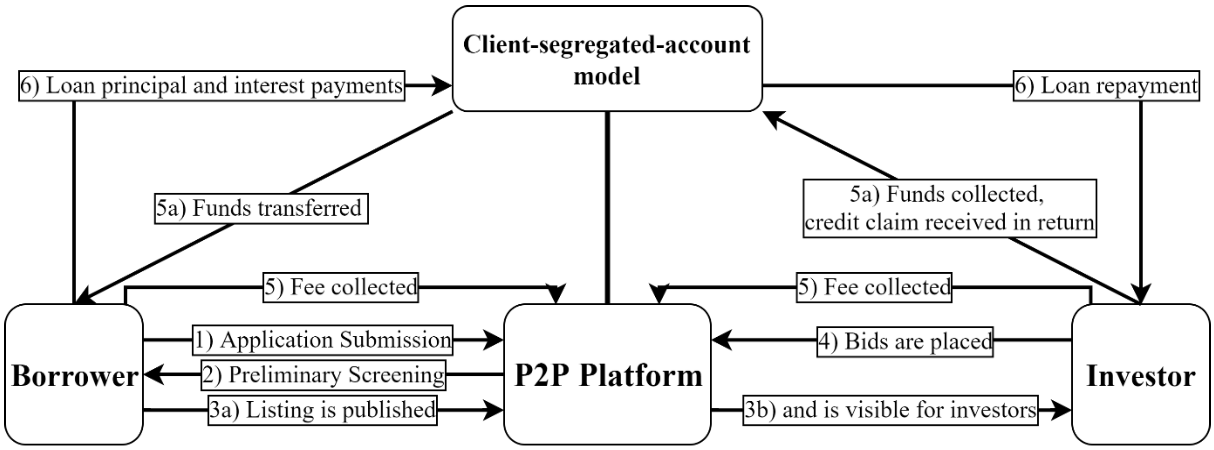
The primary function along all platforms is generally the same – to serve as a two-sided intermediary and connect the borrower with a lender. Nonetheless, there might be differences in operating mechanisms. In addition to the traditional lending platforms (e.g., Zopa, LendingClub), various platforms arise to specialize and operate in some particular industries, such as AgFunder, that is focused on the agrifood 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 from loan transactions. Moreover, several platforms do not charge anything from loan transactions.

There are several methods to categorize 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. Recently, various professional platforms focused on particular application areas are emerging. 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 allowing borrowers that are having difficulties with borrowing from traditional lenders due to an adverse credit event to receive financing through buy-to-let mortgages and bridging loans. Although to a great extent, marketplace lending consists of 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) One can split platforms into two groups: 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 has to construct a loan requirement specification list which, besides the information on creditworthiness and other necessary data depending on the platform, 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 - be successfully 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. Similar to 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 auction, the majority of platforms ended their auction process and changed the trading rule for the sake of better-quality customer service and trading efficiency, carry out the less sophisticated procedure – fundraising. Thereby, company Prosper ended its auction after five years of operating in 2010.[9] Fundraising may employ either a fixed ("All-or-Nothing") or flexible ("Take-it-All") principles of setting the funding target, which were discussed in the previous section.

Figure 3. 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 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 step borrower may reject the proposal and exit the market. Otherwise, the application is listed on the platform for a defined soliciting duration. Most of the time, while the

---

[9] 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.

individual loan listings are anonymized, institutional are published with the borrower's title.

4. To become an investor, one has to sign an agreement with the platform and complete the due diligence proceeding as a part of the Anti-Money Laundering Rules. Investors are anonymized 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 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 and Verdier 2018):
    a. In the "client-segregated account" model, mostly exercised by U.K. 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 U.K., in the U.S. and most European countries, different national banking regulations apply: 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 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 ban. Bank, then, 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 account of lenders to a debt-collecting agency for an agreed price to partially recover the credit claim. Others have developed automated litigation and recovery processes for defaulted credit lines. In the latter, the recovery rates are higher.

Similar to 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 in case of 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 contemporary structure of social media services leads to an inevitable individual's digital social footprint in the form of social media activities, preferences, age, education, social circle, etcetera. This 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, provided the proper software architecture, 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. It is not the case of marketplace lending companies 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%.[10] 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.

3. Peer-to-peer lending model in alternative finance markets

3.1. 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 case of a well-diversified portfolio containing a high number of loans. At this point, investors may benefit from diversification software instruments available that may process automatic order placement depending on the preset amount invested per loan, risk grade, maturity, etc.

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

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[11])	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%

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 at the demand and without a fee. Despite the existing secondary marketplace lending market, there is no guarantee of exit without high expense as a result of a discount. Moreover, according to the E.U. Directive on Deposit Guarantee Schemes, deposits on bank accounts at E.U. banks are guaranteed by E.U. 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, similar to one present in 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 bad debt or recession.

The significant part of platforms makes publicly available their up-to-date statistics (including annualized returns, projected and historical bad debt rates, lifetime default rates, the

[11] Personal loans

volume of buffer fund, etc.) 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. In conjunction, 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 explained 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 additional source of funding. 21% of Funding Circle customers report that they wouldn't be able to access the funds through a bank.[12] 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 are, 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 that they will get the required funds even if a platform accepted 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

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

the offer becomes attractive enough. The next shortcoming of the marketplace model is that credit risk assessment lacks disclosure; borrowers are not aware of 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.

3.2. Types of risk exposure involved in P2P lending

Before the market-by-market analysis of adequate regulatory framework, the understating of risks involved at each stage in marketplace lending intermediation, and that may create obstacles for prospective development, is inevitable.

The problem of credit risk arises due to the undeveloped appraisal marketplace lending procedure. In the case of traditional banking credit appraisal, the latter possesses access to the massive set of real historical data on a particular borrower's credit repayment performance. In some cases, banks may agree upon establishing a traditional credit information bureau (e.g., *Biuro Informacji Kredytowej* in Poland) to share the information of current and repaid loans and reduce the degree of information asymmetry featuring in the lending process. Therefore, the bank's responsibility for credit management and loan examination is justified. In contrast, P2P platforms frequently reveal only part of the borrower's information when taking into consideration of preventing investors' loss. Moreover, a borrower with fraudulent intentions may provide knowingly false information about his assets, liabilities, or creditworthiness, taking advantage of the loophole of information asymmetry in the marketplace lending model.

On the one hand, the benefits of the network information technology are indisputable; it creates a foundation for P2P market functioning. On the other hand, much greater involvement of the Internet than that of traditional credit creates exposure to the ever-present dangers of fraud, cybercrime, and operational outages. These vulnerabilities and possible loopholes create an information risk in the form of personal data leaks and the collapse of the entire platform.

The absence of regulation and legal requirement for management and staff qualifications and professional qualities of the operators brings the problem of platform risk and increases the risk of information asymmetry and misled investors. There is an illegal funds diversion hazard in case of the failure of the platform controls, control mechanism, or IT system in the P2P company. Also, as the industry develops, almost certainly certain platforms will fail to accomplish scale necessary to cover fixed costs and will be forced to shut down. The further situation with lending on a terminated platform is still under the question, which should be resolved before such an outcome turns out with potentially harmful effects for the P2P platform.

There are questions of developing higher degrees of transparency and operational standards dealing with the recovery of defaulted loans. Maximum recovery in the event of loan default is obtained through exercising claims on security or reaching an agreement with borrowers on loan rescheduling in case of unsecured loans. Banks have specialized units to carry out such tasks. Some platforms put to use special recovery programs. Still, the lack of consistent regulation leaves the degree of activity of this kind that shall be carried out by P2P platforms to minimize post-default loan losses ambiguous.

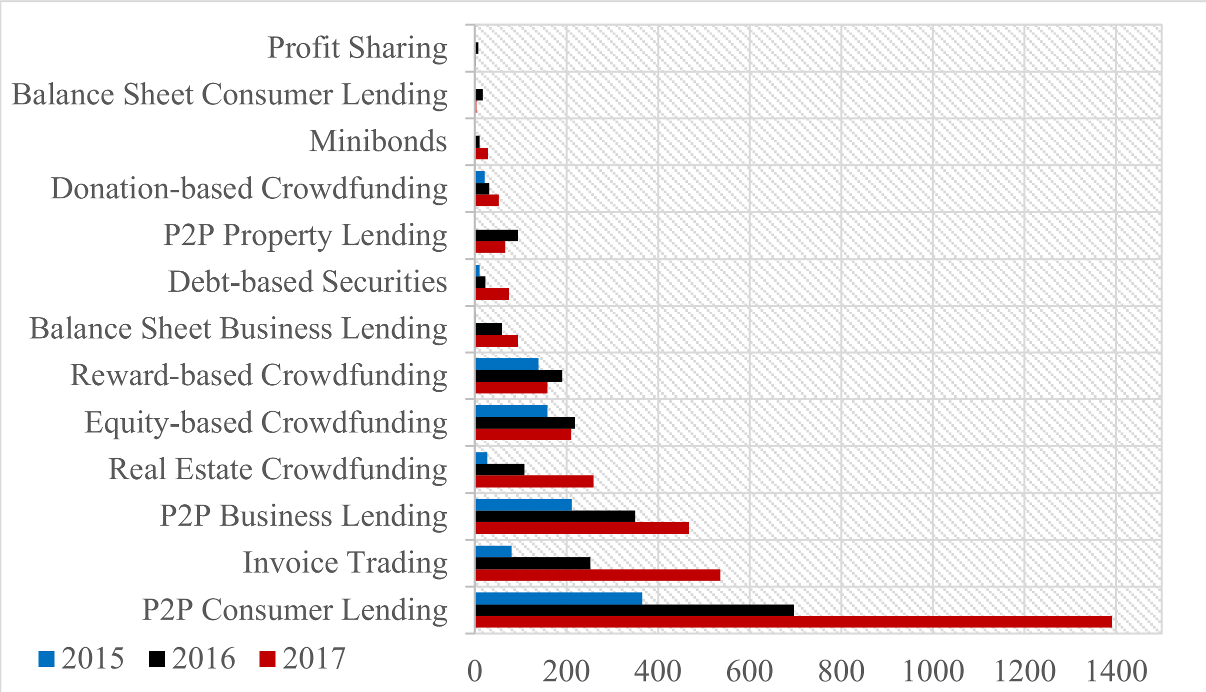
Although the P2P platforms position themselves as intermediary information agencies, the model of funding associates them with some features of financial institutions. In some countries, there is no control over the capital flows and operation situation, which makes the P2P industry spontaneous and out-of-order as a whole. In addition to the imperfect legal framework for the P2P market, some platforms are on the margins of the existing law and, in some cases, even infringe the law, thus creating regulatory and judicial risks. For instance, once the demand for loanable funds is converted into a financial product, there is a risk of attracting the investors' capital and thus, creating a capital pool within one platform.

Liquidity risk increases along with the platform's volume. In contrast to banks and other legally authorized financial institutions, the P2P industry is still in a disintegrated situation due to the absence of adequate regulation. Once a platform faces a more enormous systematic and payment risk, there is an exposure to investors’ run. Furthermore, part of P2P companies ensures the principal of the lender. Thus, there is a hazard of liquidity issues and the risk of break down when the amount guaranteed by P2P companies exceeds their solvency.

3.3. European Union market and regulation

Ever since 2013, the P2P Consumer Lending model has taken on the role of the leading branch of marketplace lending, keeping the primacy in transaction volume across Europe. As of 2017, its market share amounted to 41%. The majority of the other alternative finance activities existing in Europe have preserved the proportionality of their market shares from year to year. On the contrary, the market share of P2P Consumer Lending has expanded from 34% to 41% in 2016 and 2017 years, respectively.

Figure 4. Alternative Finance Volume in Europe (excluding the U.K.) 2015-2017 in € millions



Source: Tania Ziegler, Rotem Shneor,Karsten Wenzlaff, Ana Odorović, Daniel Johanson, Rui Hao, and Lukas Ryll. 2019. Shifting Paradigms. The Fourth European Alternative Finance Benchmarking Report, Cambridge: The Cambridge Centre for Alternative Finance (CCAF).

P2P Consumer Lending has experienced substantial aggregated growth of 99.8% and increased from €697 million in 2016 to €1,392 million in 2017. For the most part, this growth is because large incumbent platforms have expanded their operations internationally. That is, the dataset provided by the Cambridge Centre for Alternative Finance (CCAF). Comprised 73 individual P2P Consumer Lending operating platforms, 35 of which were based across Europe, including nine which serve at least in two countries; in other words, almost 26% of European firms are operating in multiple jurisdictions.

P2P Business Lending has demonstrated less impressive values of growth, yet increasing by 33% from €350 million to €467 million in 2015 and 2017, respectively. There were 90 entries from 53 distinctive firms in the European region. Among these 53 firms, 21% percent carry out activities in two or more countries. 69% of firms functioned exclusively in the business lending subdivision; meanwhile, the outstanding 31% had carried out actions in related branches of marketplace lending such as Consumer, Property, or Invoice lending.

P2P Property Lending has dropped off by €28 million, with aggregate volume decreased by 30%, constituting €67 million in 2017. It is worth noting that in preceding years, Property and

Business models of marketplace lending were closely related. Platforms that were running activities for the most part in P2P Business Lenders were simultaneously offering property-backed solutions to their business clients. However, in 2017, the number of firms operating in both branches has diminished significantly, with those firms concentrating mainly on unsecured business lending. To some extent, this process of specialization on unsecured rather than secured lending by firms that are primarily business lenders explains the data. Another clarification is the lack of distinguishing between P2P Property Lending and P2P Business Lending by some platforms operating in Business Lending, thereby generating distortion of reported statistics for these two subdivisions. However, the transaction volume of firms operating predominantly in property-based lending has increased in comparison to the preceding years. It is expected that up-to-date reports of 2020 will disclose it, presenting stable growth of transaction volume of firms majored in Property Lending.

Despite Capital Markets Union (CMU) - European Commission's plan to create a bespoke and unified framework that will promote adequate supervision and regulation of crowdfunding, crowdinvesting, and marketplace lending, a genuine single capital market in the E.U. is still lacking.[13] Regulatory and supervisory institutions of some Member States have established procedures to facilitate and support innovative business initiatives and work out their specific issues by cooperating. Regulatory sandboxes — are such initiatives, they serve as "hubs", to guide adequate regulation and supervisory measures, while these businesses are testing their actions and activities. E.U. Commission states that due to the small relative volume of lending-based crowdfunding in comparison to other financial sectors and low level of cross-border activity a dedicated centralized E.U. regulation is not necessary: "*Given the predominantly local nature of crowdfunding, there is no strong case for E.U. level policy intervention at this juncture."*[14] In this manner, E.U. Directives are implemented on the level of national law of E.U. countries. The regulation of alternative finance in the E.U., therefore, remains the objective of federal legislators and national supervisory institutions. This argumentation, however, remains open to discussion as a unified legal framework across the E.U. would unlock market opportunities and stimulate the development of FinTech businesses. Moreover, that would significantly increase the size of the market, which, as discussed, is a necessity for a platform's economic performance. On the other hand, this would mean that, previously limited to local

---

[13] European Commission's Website. 2020. "Action plan on building a capital markets union" www. ec.europa.eu

[14] Commission Staff Working Document. 2016." Crowdfunding *in the EU Capital Markets Union."* Brussels

and, perhaps uncompetitive, funding solutions, borrowers will gain access to the international market. Lenders will enjoy international investment opportunities in the same manner.

The European Banking Authority (EBA) published a document to overview the existing E.U. Directives. The Payment Service Directive (PSD) covers the payment-related side of lending-based crowdfunding yet fails to deal with purely lending-related features (i.e., platform's method of credit risk assessment, safeguards against platform default, etc.).[15] EBA highlights the current tight spot of national legislators and supervisory units. In essence, P2P lending platforms dismantle present models of business into smaller pieces and reconstruct them, creating a brand-new business model. The existing regulations cover some portion of aspects; there are, however, characteristics specific to new models that need treatment and the approach of modifying and/or adjusting existing directives and policies may result in a disintegrated legal framework and possible gaps in regulations.

According to the abovementioned issues, national approaches towards regulating marketplace lending platforms are developing at different paces in different E.U. member states. Currently, 9 E.U. member states, namely Austria, Belgium, Spain, France, Italy, Germany, Portugal, Finland, and Lithuania, have bespoke regulatory systems for crowdfunding. Among them, Spain, France, and Portugal have regimes specially designed for lending-based crowdfunding. Before the Brexit procedure was completed, the U.K. was in the list of E.U. states with bespoke systems. Other E.U. member states have tried to tailor existing national banking and financial legal code to fit the new demands, regulatory frameworks of those countries have several gaps that are as a rule associated with platform-specific risks, such as the situation when platform shuts operations down its operations is yet for the most part unregulated. Frequently platforms based in countries lacking distinct FinTech supervision are not required to obtain central authorization from the national financial supervisory institution to set off business activity and are not subject to comply with minimum capital requirements.

Countries with specially-designed legal systems for lending-based crowdfunding are considerably more progressive in their regulatory methodologies. In those countries, platforms need a central authorization to start a business, they must fulfill minimum capital requirements, and they must have resolution plans in place in case the platform bankruptcy. In contrast to "tailored" regimes, these take account of Know-Your-Client (KYC) principles, although the

[15] European Banking Authority, "Opinion of the European Banking Authority on lending-based crowdfunding", EBA/Op/2015/03

client information requirements somewhat differ. According to the European Commission (E.C.) Staff working document, in Spain, *"Platforms must assess the experience and knowledge of its clients and verify that they can take their own investment decisions and understand and prioritize information risks.*[16] In France, access to platforms is restricted to registered investors who have been warned of and accepted risks. Moreover, in case of investment is not in line with the investor's experience, the platform shall refuse the latter's subscription; appropriateness and suitability tests are also foreseen for borrowers. Under the majority of bespoke regimes, a passport is required to be granted access to the platforms registered under the MiFID[17]. In contrast to the U.K., in all E.U. member states with bespoke regimes, the maximum investable amounts apply. In this manner, under French regulation: *"Lender can finance up to €2,000 per project if financing is in the form of a loan with interest and up to €5,000 per project for an interest free loan.*[16]

Despite the specificity of bespoke regimes, there are still a couple of issues that are not addressed. The amendment to the existing legislature shall provide transparency on the processing of borrowers' personal data performed for credit assessment purposes to prevent the threat in the form of discrimination. The second issue is related to equal treatment of investors, providing equal opportunities regardless of the invested volume and ensuring that institutional investors are not treated favorably. Thus, establishing an investment limit for institutional investors per loan to prevent an excessive inflow of institutional funds to the marketplace lending market and possible evasion of stricter financial supervision present in centralized capital markets and exchanges.

3.4. The United Kingdom market and regulation

Given the U.K. market, the main portion of total online alternative finance volume is P2P Business Lending; it accounted for £2.039 billion in 2017. During the preceding seven years, as stated by Cambridge Centre For Alternative Finance (CCAF), the Business branch of marketplace lending has generated a volume of £5.17 billion, that is, 39% of that was created in 2017. The year-over-year growth amounted to 66% in 2017. The percentage of applications that were approved to be published on the platform - so-called the onboarding/qualification rate,

---

[16] Commission Staff Working Document. 2018." Proposal for a regulation of the European Parliament and of the Council on European Crowdfunding Service Providers (ECSP) for Business and Proposal for a Directive of the European Parliament and of the Council." Brussels

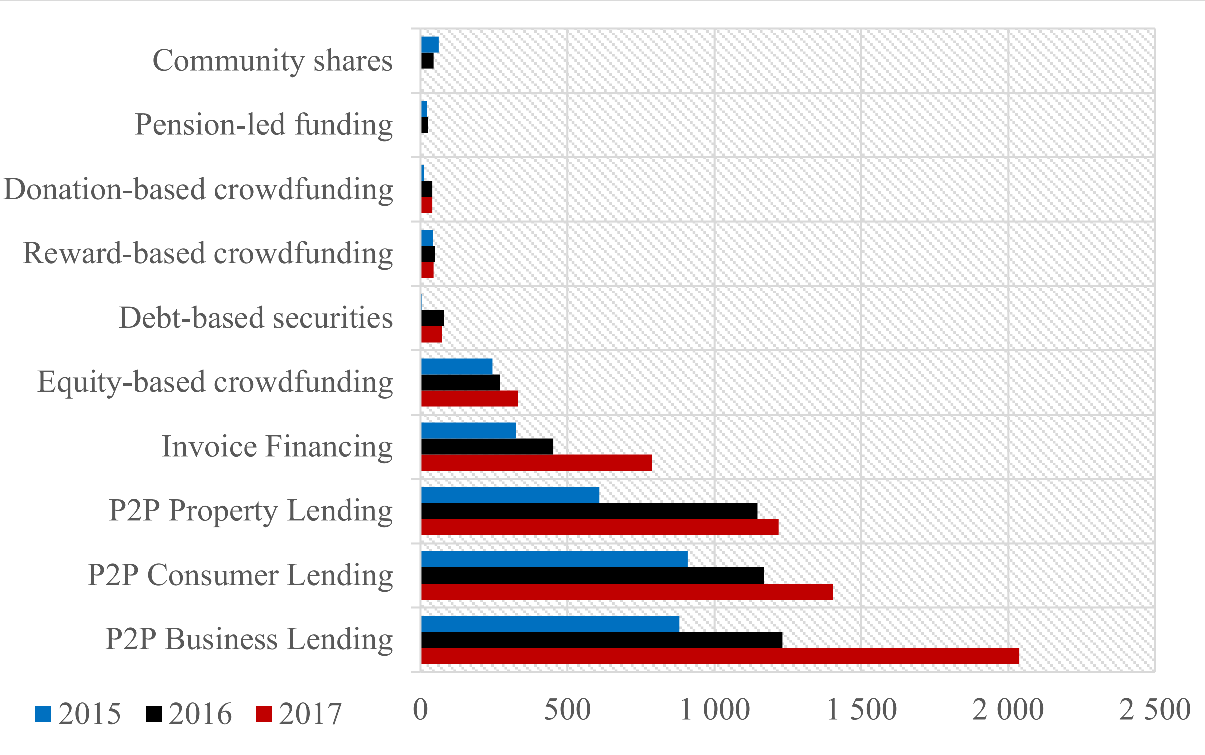
[17] The Markets in Financial Instruments Directive

experienced a substantial falloff in 2017 and corresponded to 12%; in contrast, in 2016, this indicator was 38%. (Zhang et al. 2018) Nevertheless, as soon as the fraction of applications of those qualified to fundraise, which managed to receive funds (also referred to as successful funding rate), soared from 31% in 2016 to 96% in the following year. In 2017 the fraction of borrowers who succeeded in raising funds at least twice amounted to 12%. The percentage of repeat investors on the platforms was at around 89%. The automated investment selection instruments earned noticeable acceptance among investors. Explicitly, the share of investors making use of these instruments grew from 61% in 2016 to 97% in 2017. As reported by CCAF, the significant increases in the number of defaults and fraud threat were the highest risks faced by platforms with 20% of platforms classified it as very high risk.

Identical to 2016, P2P Consumer Lending is the second largest contributor to the alternative finance market volume with an output of £1.4 billion in 2017 and year-over-year growth of 20%. Similar to Business Lending, the percentage of investments with the involvement of auto-selection tools reached 99% in 2017. Platforms expressed their concerns about potential changes in regulations: 33% of platforms defined it as high and 17% as very high risk. The problem of malpractice faced by a business was reported by 17% of platforms as very high and by 50% as high.

Similar to last year, P2P Property Lending stand for the third largest division of the alternative finance industry of the U.K. in terms of volume. Its volume made up £1.218 billion in 2017, a 6% increase in 2016's volume. The qualification/onboarding rate for 2017 expanded year-over-year to 33.6%. From that who met the criteria to apply for a loan on the platforms, 74.6% succeeded in raising funds, 9.4% lower from last year's rate. The intensity of use of auto-selection tools fell radically and was lowest among the triplet of branches in 2016 (60%) and 2017 (43%). The proportion of repeat investors was comparable to Business Lending - 86%. Property Lending platforms had the highest rate of repeat borrowing in marketplace lending in 2017 - 34%. 100% of surveyed platforms assigned malpractice as at least medium risk, meanwhile cyber hazards were viewed by 16.67% of platforms as very high and by 41.67% as high.

Figure 5. Alternative Finance Volume in the United Kingdom 2015-2017 in £ million



Source: Zhang, Bryan, Tania Ziegler, Leyla Mammadova, Daniel Johanson, Mia Gray, and Nikos Yerolemou. 2018. The 5th U.K. Alternative Finance Industry Report. Industry Report, Cambridge: The Cambridge Centre for Alternative Finance (CCAF).

The regulatory commitment is made by the Financial Conduct Authority (FCA); it assesses platforms on an individual basis and issues operating authorization. Analogous to the E.U. zone, FCA practices regulatory "sandboxes", heavily reliant on providing information on future regulatory amendments, as well as allowing some platforms to test new supervisory features and market regulations. FCA collects feedback from platforms that facilitates the practice of identifying organizational shortcomings and risks. The FCA emphasizes the problem of regulatory arbitrage: there is a risk that P2P lending platforms may implicitly carry out activities similar to that conducted by traditional financial institutions, and yet benefiting from the relatively less strict regulations.[18] Among other issues, FCA addresses the concept of credit risk pooling, platforms that are carrying out asset management, and dealing with maturity mismatch. The FCA has declared that it continuously observes the market. In case of any detriment caused to investors or borrowers, it would take actions to prevent the interests of P2P lending customers. The FCA also expresses concerns regarding insufficient directives in event platform

[18] Financial Conduct Authority. 2016. Interim feedback to the call for input to the post-implementation review of the FCA's crowdfunding rules. Feedback Statement, London: Financial Conduct Authority.

defaults and probably negligent supervision of provision funds that may bring disturbance in investors' incentives to reduce risk. Apart from the above flaws, the current supervisory approach of FCA comes into view as adequate and suitable for the new state of affairs. Despite the high pace of development in industry, authorities in the U.K. are reasonably reactive to the arising problems and risks; their measures conform with the industry growth and apparent subtleties. At the same time, the regulatory formalities set by FCA have not inhibited the industry development and prosperity.

4. Method of scorecard credit risk assessment

4.1. 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 particular 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 "good", since they may benefit from extensive client data collected from their experience or access databases of credit information bureaus[19]. 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 some loan and borrower's feature 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[20] range, and many more. Besides, 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 a quite 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

[19] 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 also some non-bank lending companies.

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

applications, thus minimizing the survivorship bias risk[21]. 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 produce fewer errors.

In the classical credit scoring approach, there two types of scoring techniques: application and behavioral. The principal difference is that the application scorecard (AS) is created for a specific lending company and particular product (e.g., revolving loans, mortgage loans) and utilizes its historical data to evaluate at the application stage. They may include such characteristics as personal data, application data[22] , 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.[23] The number of variables in scorecard should lay in between 8 and 15 to provide stability and keep relatively high predictive power even if the profile of one or two variable changes. Scorecards with an insufficient number of characteristics are more vulnerable to minor changes from the applicant's profile, making the scorecard unable to sustain stable over time.[23] Recent researches confirm 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 cutoff score – the final sum of scores for each attribute present in the scorecard for a particular application. There are various techniques to determine specific scores and cutoff points. Generally, these methods are divided into parametric – ones in which the number of parameters is finite and fixed with respect to data (e.g., linear regression), and non-parametric – ones in which the potential number of parameters is independent of data and may potentially be infinite (e.g., decision trees, neural networks).

---

[21] 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.

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

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

This paper is going to focus on parametric statistical techniques, 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 is of 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: 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 (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 case of one independent variable $p(\mathrm{X}) = \Pr(\mathrm{Y} = 1|\mathrm{X})$, where Y is dependent, and X is independent variables. Parameters reflect the relationship between explained and explanatory variables, such that: $p(\mathrm{X}) = \beta_0 + \beta_1\mathrm{X}$. Fitting a straight line would be inappropriate in case of a binary outcome; therefore the sigmoid-shaped function is used: $p(\mathrm{X}) = \frac{e^{\beta 0+\beta 1\mathrm{X}}}{1+e^{\beta 0+\beta 1\mathrm{X}}} = \frac{1}{1+e^{-(\beta 0+\beta 1\mathrm{X})}}$; alternative form is $\frac{p(\mathrm{X})}{1-p(\mathrm{X})} = e^{\beta 0+\beta 1\mathrm{X}}$; 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 $p(\mathrm{X}) = \Pr(\mathrm{Y} = 1|\mathrm{X})$ correspondingly. Taking the natural logarithm of both sides gives the logistic regression function (logit): $\ln(\frac{p(\mathrm{X})}{1-p(\mathrm{X})}) = \beta_0 + \beta_1\mathrm{X}$. Similar to CLRM, a one-unit increase in X increases the value of LHS (logit) by β_0. The change in conditional probability, $p(\mathrm{X})$, depends on the value of an independent variable. For multiple independent variables: $p(\mathrm{X}) = \frac{e^{\mathrm{X}\beta}}{1+e^{\mathrm{X}\beta}}$; 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}.

4.2. 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 smbinning package. The initial dataset 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 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 a large amount of data is resource-consuming. Therefore, after removing listings with missing information, 400000 observations were randomly selected from this dataset. An additional binary variable (good/bad flag) "DEF" was introduced with values 1 for bad loan outcome and 0 for good loan outcome.

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[24]: "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 $ U.S. **Numerical variable**.
avg_fico[25]	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 $ U.S. **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".

[24] Initially variable contained level "Other", which has been omitted.
[25] Generated as an arithmetic average of "last_fico_range_low" and "last_fico_range_high" variables.

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[26]	The self-reported annual income in $ U.S. provided by the borrower during registration. **Numerical variable**.

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 a quite diverse dataset with diverse applicants.

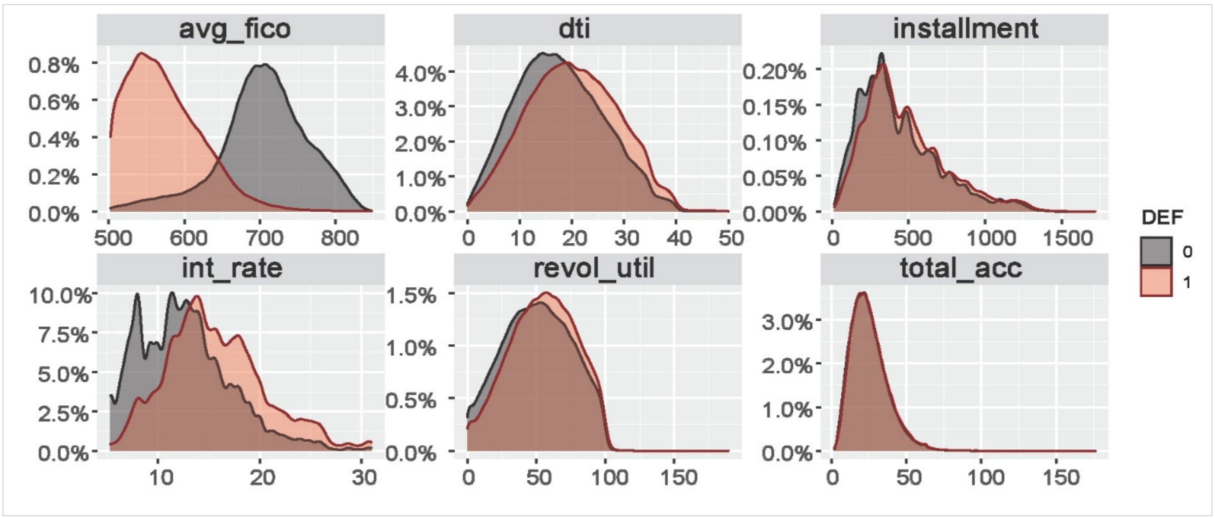
Table 3. Descriptive statistics for independent numeric variables

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.

[26] Observations only with verified annual income are included in the final dataset.

Figure 6. Kernel density estimations for selected numeric variables

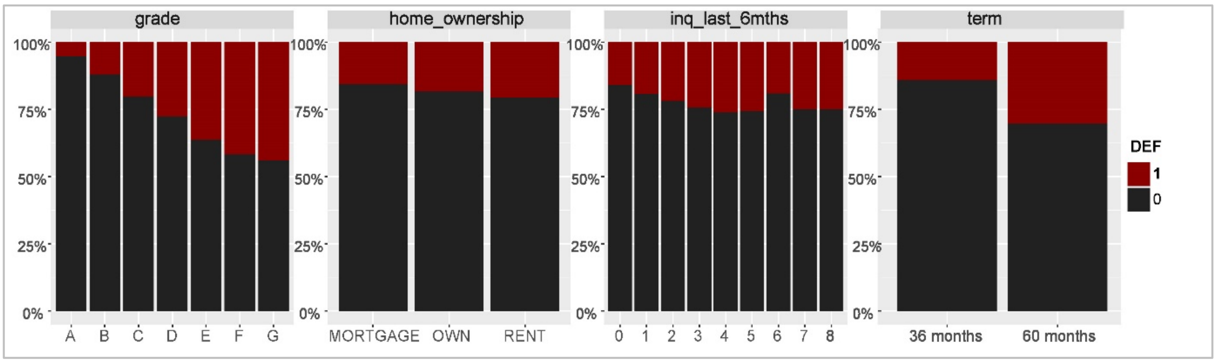


Source: Own study based on: LendingClub Loan Data. San Francisco, February 2020. Database. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

Figure 6 consists of kernel density approximations for several continuous variables by loan outcome. Despite the generally positive (right) skewness tendency, the majority of variables are approximately bell-shaped. Already at this step, conclusions about the data may 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 7 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 7. 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 last 6 months is an ordinal factor variable, and the general relation in positive, the percentage of defaulted loans grows as the number of inquiries increase; however, there is an apparent nonlinearity in from of bad rate drop created by level "6".

4.3. 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 to proceed 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 relation 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, such 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.

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.

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, it discloses the relationship between dependent and explanatory variable and may be calculated for i-th bin as $WoE_i = \ln\left(\frac{\%\text{ of non-defaults}_i}{\%\text{ of defaults}_i}\right)$.[27] 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.

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[28] 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 training 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, training sample contains 70% of observations, and the percentage of defaulted loans is equal to 18%.

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 more advanced technique. Package smbinning 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

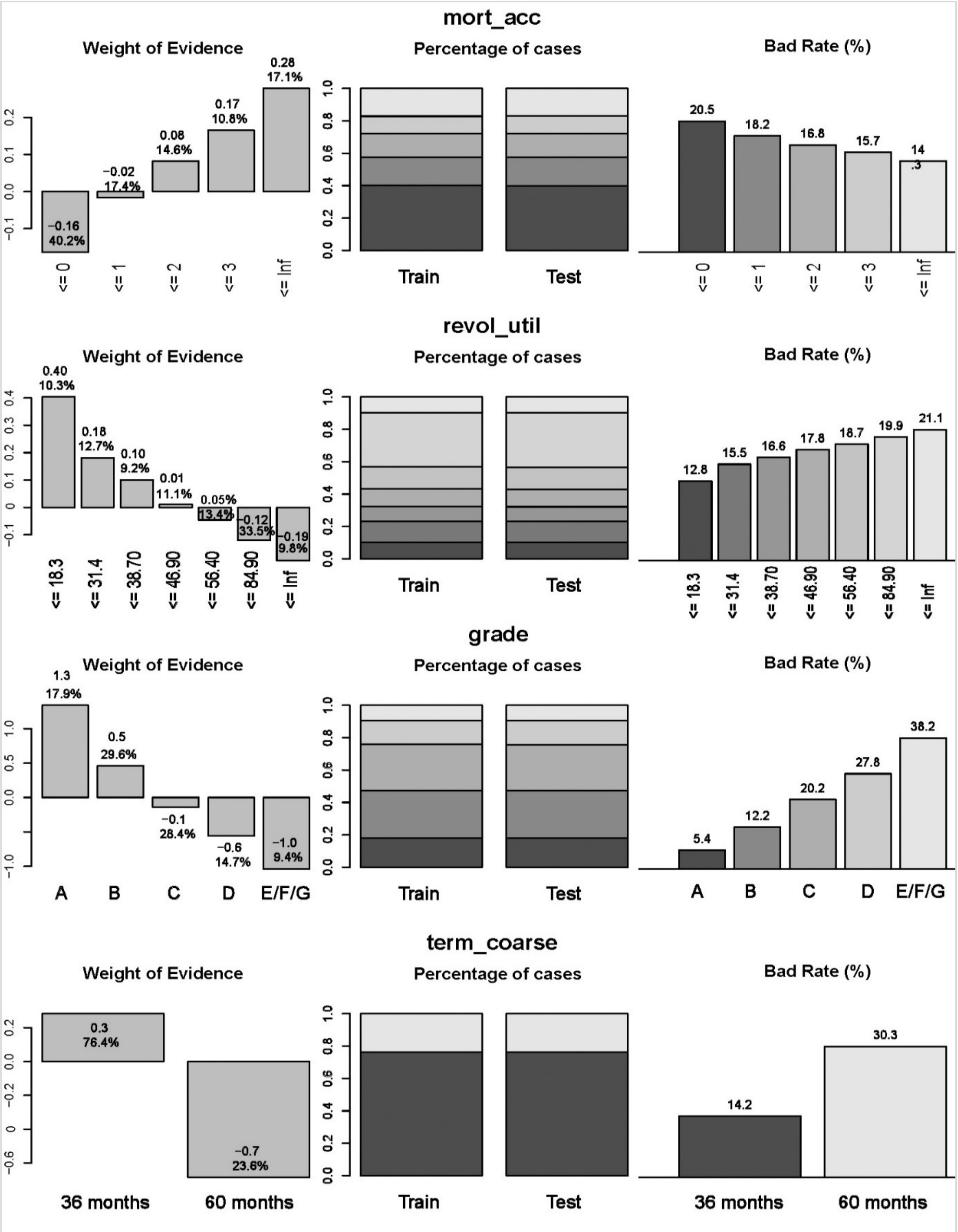
---

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

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

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 8 and 9. 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.

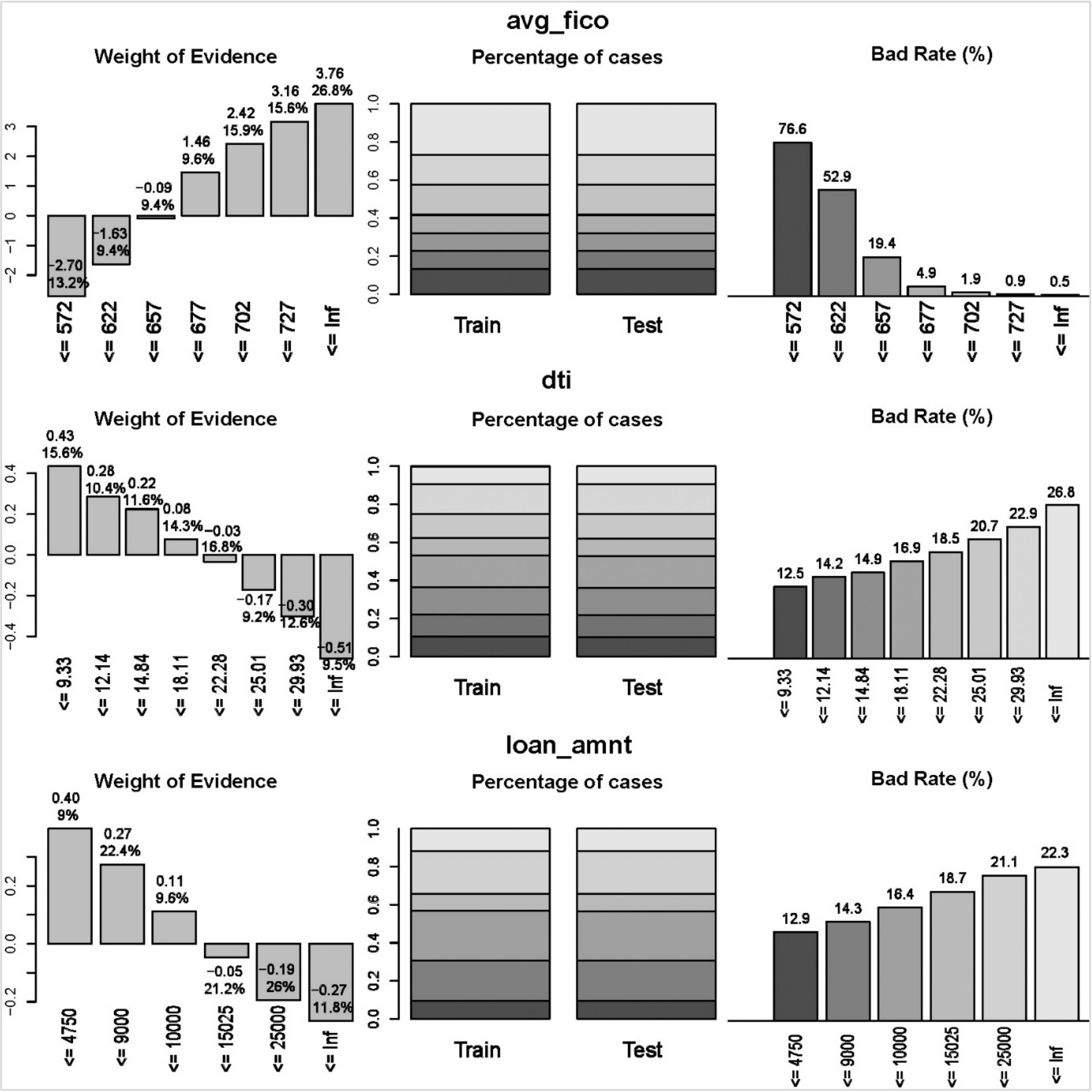
Figure 8. Summary graphs of Coarse Classing, part I



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.

Figure 9. 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 comparably similar 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 the 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.

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.

4.4. 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:

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

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.

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. Logistic Regression quality assessment summary

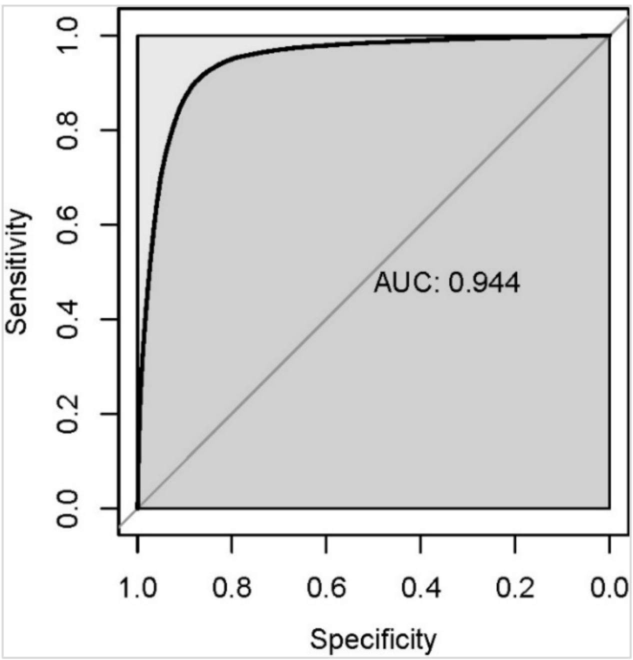
LR	**Osius-Rojek**	**Hosmer-Lemeshow**	**Pearson's Test**	**ROC Comparison**
0	0	0	1	0
K-S Statistic Train	**K-S Statistic Test**	**Population Stability Index**		**K-S Stability**
0.7793	0.7779	0.0003		0.9171
GINI Train = 0.8881		**GINI Train 95% CI: [0.8860; 0.8902]**		
GINI Test = 0.8891		**GINI Test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

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.

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.

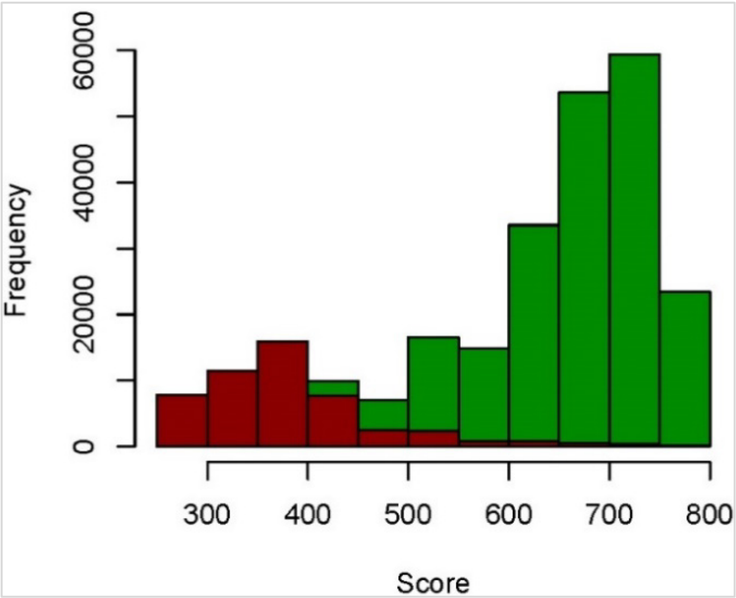
Figure 10. Receiver operating characteristic (ROC) curve in specificity and sensitivity space



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

The area under the ROC curve (AUROC) presented in figure 10 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 11. 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.

Figure 11. 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:

$$points_{i,j} = \frac{\widehat{B_j} * WoE_{i,j} * PTD}{\ln(0.5)}; \quad points_{intercept} = \frac{\ln\left(\frac{1}{e^{B_{intercept}}}\right) + \ln(ODDS) + \frac{\ln(2)*PS}{PTD}}{\ln(2)/PTD}$$

where:

$points_i$ – points subject to i-th level of j-th variable, $\widehat{B_j}$ – an estimate of j-th feature.

$WoE_{i,j}$ – WoE of i-th level of j-th variable.

$points_i$ – points subject to constant (initial score).

$B_{intercept}$ – value of intercept.

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
- maximizing $F1\ Score = \frac{2*TP}{2*TP+FP+FN}$
- maximizing $Cohen's\ Kappa = \frac{Accuracy - P_e}{1-P_e}$[29]
- maximizing $Matthews\ Correlation\ Coefficient\ (MCC) = \frac{TP*TN-FP*FN}{Sqrt((TP+FP)*(TP+FN)*(TN+FP)*(TN+FN))}$.

Values of cut-off points subject to each method are calculated based on 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

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

outcomes; meanwhile, the share of correctly predicted Positive outcomes is higher in Cohen's Kappa approach.

5. 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. In addition, the outline of the contemporary country-specific legal frameworks was presented in UK and EU.

Marketplace lending show itself as one of the most promising and rapidly emerging forms of crowdfunding. It experienced a massive development in recent years, providing 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 method of credit scoring was checked for the applicability in the marketplace lending. 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 there is a sufficient both historical data and application-specific data available.

Moreover, the research has shown that logistic regression approach to scorecard development provides fairly high AUROC values as well as sensitivity and specificity statistics that are comparable even 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 there might be not 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 shall select the preferred cut-off point subject to their risk acceptance level. As follows, the latter two methods are the only 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 subject to the highest expected profit.

The recent COVID-19 pandemics caused by SARS-CoV-2 virus has brought a noticeable disturbance to the financial market and its lending division in particular. The operational side of online platforms remained virtually unaffected, and employees continued their work remotely. Nevertheless, P2P lending platforms have faced some kind of a "bank run". A particular share of investors, based on the experience and fear of 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 an increased number of defaults, since investors carry 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 well as the notion of deferred repayment solutions introduced by platforms for SMEs that are experiencing liquidity issues.

References

Bellefamme, P., T. Lambert, and A. Schwienbacher. 2010. "Crowdfunding: An industrial organization perspective." *Prepared for the Workshop Digital Business Models: Understanding Strategies' held in Paris on June 25–26.*

Chen, Dongyu, Fujun Lai, and Zhangxi Lin. 2014. "A trust model for online peer-to-peer lending: a lender's perspective." *Information Technology and Management* 239-254.

Crockett, Zachary. 2019. "Kickstarter: A data analysis." *the HUSTLE.* February 10. Accessed Decemder 23, 2019. https://thehustle.co/archive/02102019d.

Financial Conduct Authority. 2016. *Interim feedback to the call for input to the post-implementation review of the FCA's crowdfunding rules.* Feedback Statement, London: Financial Conduct Authority.

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

—. 2019. *Statistics.* December 31. Accessed February 7, 2020. www.fundingcircle.com/uk/statistics/.

Gerber, E. M., J. S. Hui, and P. Y. Kuo. 2012. "Crowdfunding: Why people are motivated to post and fund projects on crowdfunding platforms." *Proceedings of the International Workshop on Design, Infuence, and Social Technologies: Techniques, Impacts and Ethics* II (11).

Gonzalez, Laura. 2018. *Blockchain, Herding and Trust in Peer-to-Peer Lending.* Forthcoming, Managerial Finance Special Issue on Blockchain, California State University, Long Beach.

Havrylchyk, Olena, and Marianne Verdier. 2018. "The financial intermediation role of the P2P lending platforms." *Comparative Economic Studies 60* 115–130. doi:10.1057/s41294-017-0045-1.

Havrylchyk, Olena, Carlotta Mariotto, Talal Rahim, and Marianne Verdier. 2019. "The expansion of the peer-to-peer lending." *SRNN.* August 26. Accessed December 12, 2019. https://ssrn.com/abstract=2841316.

Hu, Maggie Rong, Xiaoyang Li, and Yang Shi. 2019. "Adverse Selection and Credit Certificates: Evidence from a P2P Platform." *ADBI Working Paper Series* ADBI Working Paper 942. https://www.adb.org/publications/adverse-selection-credit-certificates-evidence-p2p-platform.

IBISWorld. 2019. *IBIS World Industry Report OD4736: Peer-to-Peer Lending Platforms in the*

US. Market research report, IBIS World.

Kritzinger, Nico, and Gary W. van Vuuren. 2018. "An optimised credit scorecard to enhance cut-off score determination." *South African Journal of Economic and Management Sciences* 21(1), a1571.

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

LendingClub. 2020. *LendingClub Loan Data.* Database. San Francisco, February. www.kaggle.com/denychaen/lending-club-loans-rejects-data.

—. 2019. *LendingClub Statistics.* March 31. Accessed February 7, 2020. www.lendingclub.com/info/demand-and-credit-profile.action.

LendingCrowd. 2020. *Marketplace Statistics.* February 6. Accessed February 7, 2020. app.lendingcrowd.com/statistics.

Lenz, Rainer. 2016. "Peer-to-Peer Lending: Opportunities and Risks." *European Journal of Risk Regulation* 688-700.

Lu, Caimei, and Lu Zhang. 2018. "Research on Risk Factors Identification of P2P Lending Platforms." *American Journal of Industrial and Business Management* (8): 1344-1357.

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.

MarketFinance . 2020. *Investor Statistics* . Accessed February 7, 2020. marketfinance.com/investor-statistics.

Möllenkamp, Nilas. 2017. "Determinants of Loan Performance in P2P." *9th IBA Bachelor Thesis Conference.* Enschede: University of Twente.

Oxera Consulting LLP. 2016. *The economics of peer-to-peer lending* . Independent economic assessment, Oxford: Peer-to-Peer Finance Association.

2019. *P2PMarketData.* October 31. Accessed December 7, 2019. https://p2pmarketdata.com.

Prosper Funding LLC. 2019. *Press Releases.* Accessed December 7, 2019. https://www.prosper.com.

RateSetter . 2020. *RateSetter statistics.* January. Accessed February 7, 2020. https://www.ratesetter.com/invest/statistics.

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.

SauermannI, Henry, Chiara Franzoni, and Kourosh Shafi. 2019. *Crowdfunding scientific research: Descriptive insights and correlates of funding success.* Utrecht: PLoS ONE 14(1): e0208384. https://doi.org/10.1371/%20journal.pone.0208384.

Serrano-Cinca, C., B. Gutiérrez-Nieto, and L. López-Palacios. 2015. "Determinants of Default in P2P Lending." *PLoS ONE 10* 10.

Siddiqi, Naeem. 2017. *Intelligent Credit Scoring: Building and Implementing Better Credit Risk Scorecards.* Hoboken: John Wiley & Sons.

Statista. 2019. *Alternative Lending.* September. Accessed December 12, 2019. https://www.statista.com.

Tania Ziegler, Rotem Shneor,Karsten Wenzlaff, Ana Odorović, Daniel Johanson, Rui Hao, and Lukas Ryll. 2019. *Shifting Paradigms.* The Fourth European Alternative Finance Benchmarking Report, Cambridge: The Cambridge Centre for Alternative Finance (CCAF).

United Kingdom: BBC. 2005. *Q&A: Online lending exchange.* March 7. Accessed November 28, 2019. news.bbc.co.uk/2/hi/business/4325761.stm.

Vallée, Boris, and Yao Zeng. 2019. "Marketplace Lending: A New Banking Paradigm?" *The Review of Financial Studies* 1939–1982.

Wang, Guifeng, Enhong Chen, and Hefu Zhang. 2017. "P2P Lending Survey: Platforms, Recent Advances and Prospects." *ACM Transactions on Intelligent Systems and Technology* 1-28.

Zhang, Bryan, Tania Ziegler, Leyla Mammadova, Daniel Johanson, Mia Gray, and Nikos Yerolemou. 2018. *The 5th UK Alternative Finance Industry Report.* Industry Report, Cambridge: The Cambridge Centre for Alternative Finance (CCAF).

Ziegler, Tania, Bryan Zhang, Ben Shenglin, Wangxin Wang, Leyla Mammadova, Rui Hao, Dan Luo, et al. 2018. *The 3rd Asia Pacific Region Alternative Finance.* Industry Report, Cambridge: The Cambridge Centre for Alternative Finance (CCAF).

Ziegler, Tania, Daniel Johanson, Bryan Zhang, Ben Shenglin, Wangxin Wang, Leyla Mammadova, Rui Hao, et al. 2018. *Reaching New Heights: The 3rd Americas Alternative Finance Industry Report.* Industry Report, Cambridge: The Cambridge Centre for Alternative Finance (CCAF).

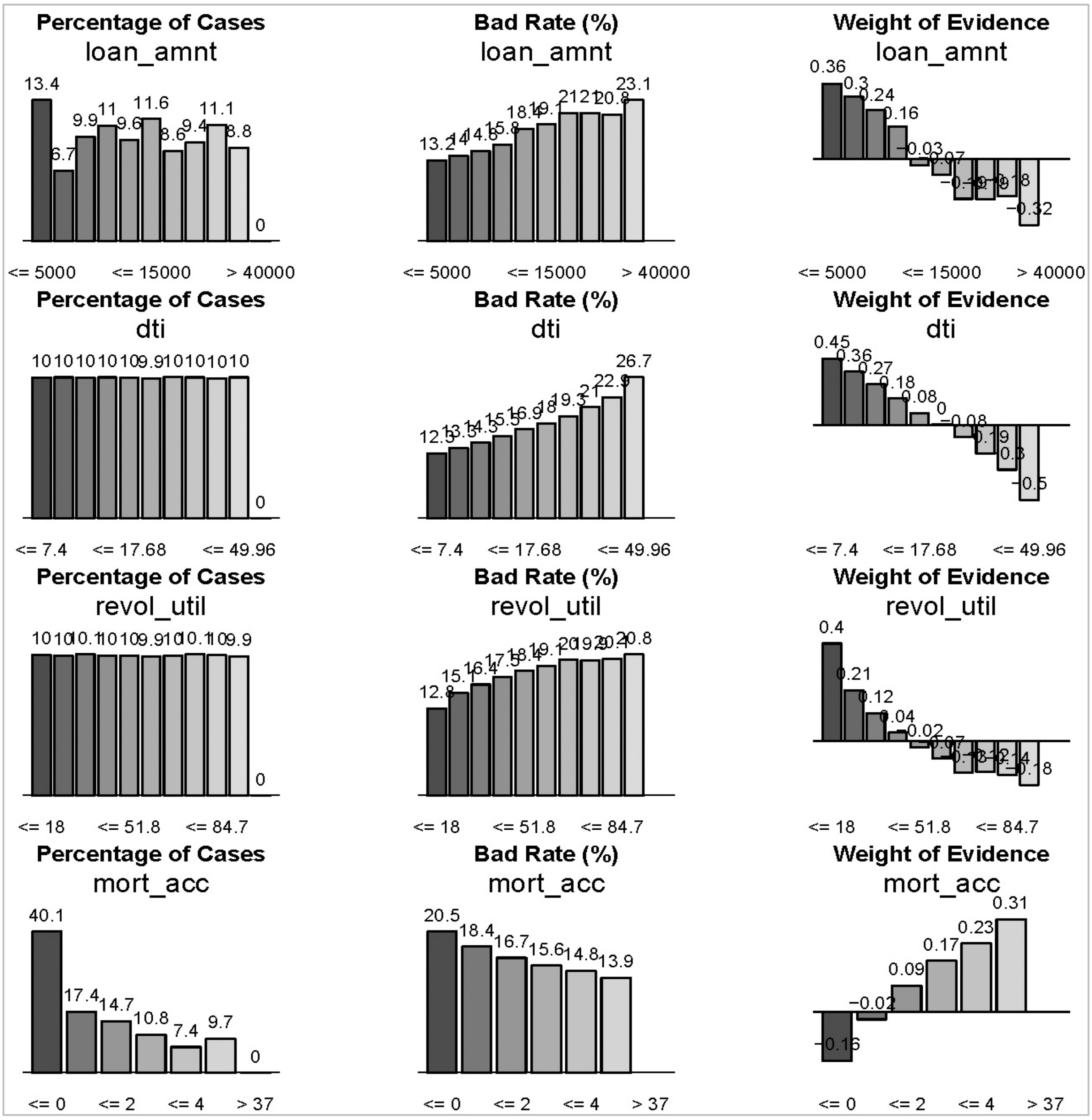
Zopa Bank Limited. 2019. *Zopa.com.* Accessed December 7, 2019. https://www.zopa.com.

Appendices

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

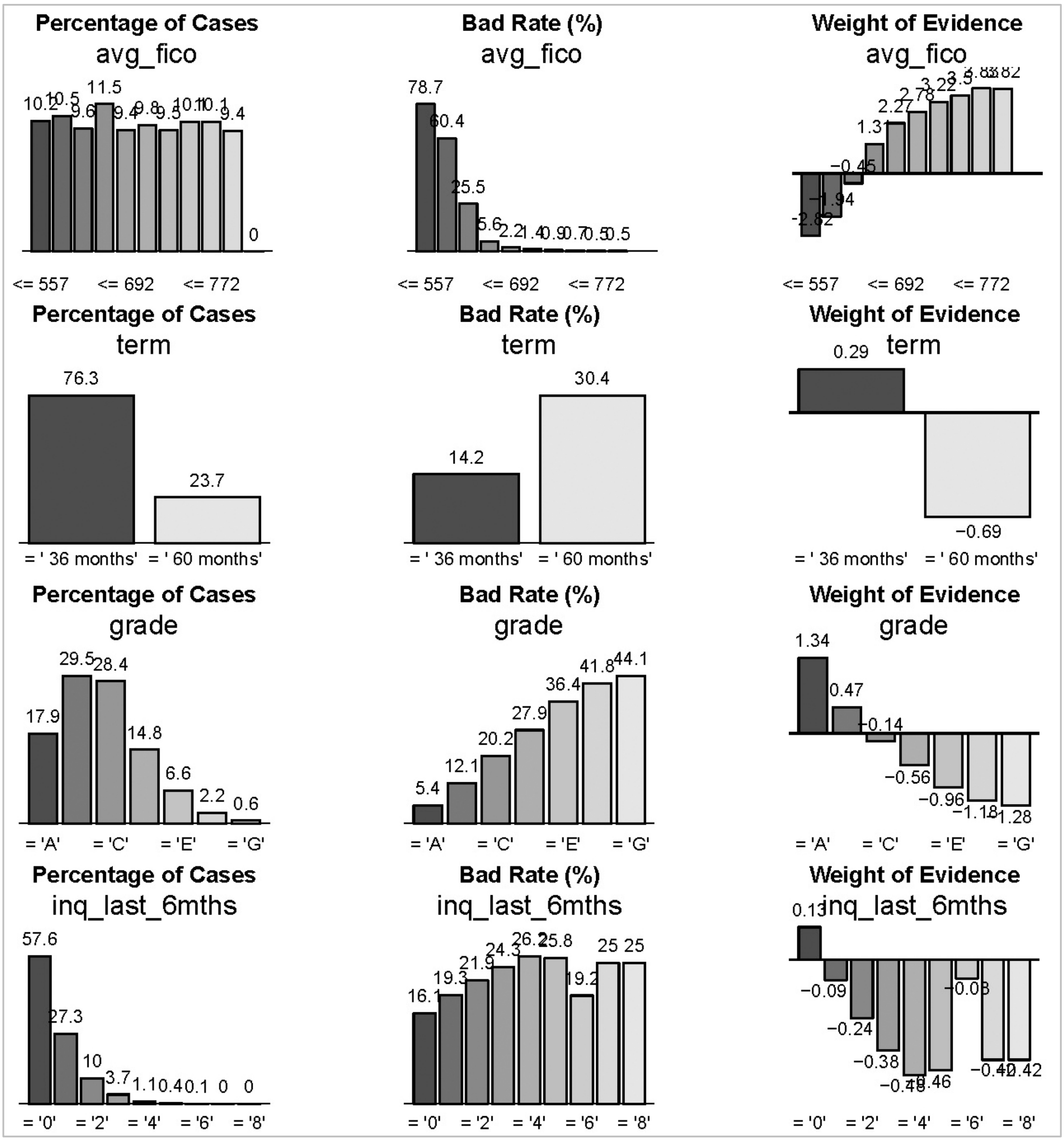
Figure 12 contains sets of 3 graphs for each variable that were picked out as a result of variable quality assessment. The percentage of cases indicates the proportion of observations that falls into the specific bin. Bad Rate illustrates the percentage of defaults (G/B flag = 1) for a particular bin. Weight of Evidence displays calculated WoE for each bin.

Figure 12. 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.

Figure 13. Summary graphs of fine 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.

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	0.361	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

University of Warsaw
Faculty of Economic Sciences
44/50 Długa St.
00-241 Warsaw
www.wne.uw.edu.pl