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Doctoral School of Business and Management

THESIS SYNOPSIS

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The new form of financial intermediation: key issues of peer-to-peer lending

PhD dissertation

Supervisor:

Barbara Dömötör, PhD

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Institute of Finance

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1. Research background and objectives

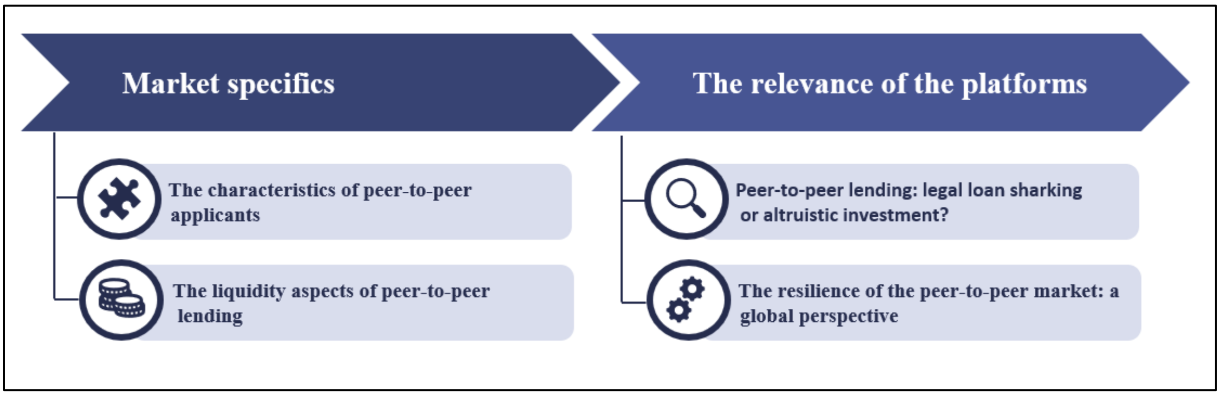
In the previous years, fintech transformation and innovative technological solutions had a significant impact on the economy. This trend reached the financial market as well. Conventional financial institutions introduced a wide range of online products and services. Besides that, a disintermediation tendency has started, and alternative funding models appeared on the market, performing capital allocation. One of this new form is peer-to-peer lending (P2P) or marketplace lending, where the traditional intermediary role is left out of the process. The main idea of the business model is that being more cost efficient, the online platforms offer more beneficial conditions for borrowers compared to a bank loan. From investor perspective the expected return is promised to be higher than a bank deposit yield. However, the risk associated with this investment is also significantly higher.

After the first platform was launched in 2005, the segment showed a robust expansion and several new players appeared on the market in many different countries. Different business models evolved: some of them provide loans only to retail borrowers while others are specialized on business lending for SMEs. The investor side is also diverse, originally retail investors lent, however later institutional investors stepped into the market, first in the United States, which led to a more robust expansion. The geographical scope of the marketplaces is also varied, large part of them allows cross-border lending, others permit only domestic participants. The products offered by the platforms are limited to different loan types such as personal loan, student loan or property loan. According to the statistics of Cambridge Centre for Alternative Finance (2021), the total volume of peer-to-peer lending reached approximately $50 billion as of 2020. The strong market growth raises several questions regarding the future of financial intermediation, the role of the platforms on the financial market and their interaction with commercial banks.

The purpose of this dissertation is to gain a comprehensive understanding regarding the relevance of the peer-to-peer lending platforms and to examine the market specific features. The thesis begins with a theoretical part where, peer-to-peer lending is defined and embedded into the literature of financial intermediation. Then the main features of the platforms are presented in comparison with the conventional banking sector, covering the relevant market imperfections. After that, the main research directions in peer-to-peer lending literature are summarized, and the current market figures are described. Finally, the theoretical part ends with an overview of the segment's regulation.

Thereafter, four different studies are presented, focusing on various aspects of the marketplaces. The first two papers are exploring the market specific features, covering the characteristics of the P2P applicants and the examination of the secondary market. The remaining two papers investigate the relevance of the platforms and their potential role on the financial market. Specifically, the information processing advantage of the marketplaces is analyzed and the market reaction in case of an external shock in the different types of economies. Figure 1 presents the above-mentioned concept.

1. Figure: The key studies presented in the dissertation



Source: by Author

The four studies, detailed in the upcoming sections aim to answer the following research questions:

- Which macroeconomic factors explain the demand for P2P lending in the US market? Which borrower groups can be differentiated based on similar patterns?
- How liquid is the secondary market based on the three liquidity dimensions of selling rate, average selling time, and discount? Which variables have a significant impact on the selling outcome, selling time, and discount rate? How does the secondary market react to external shocks (indicated by a pandemic situation)?
- Do P2P lending platforms have an advantage in information processing compared to traditional banks due to the incorporation of alternative information? What is the performance profile of P2P investments for the lenders?
- Are pre-COVID economic variables applicable to classify countries according to their market reaction to the pandemic outbreak? How does the P2P market respond to an external shock in the different types of economies?

2. Methodology and datasets used

The dissertation covers four different papers, focusing on relevant aspects of peer-to-peer lending. The upcoming sections provide a brief summary on the methodology applied and the datasets used in the analysis.

2.1 The characteristics of peer-to-peer applicants[1]

The first study explores the platforms from borrower perspective. To obtain a comprehensive understanding of the fast-growing market of peer-to-peer lending, the demand coming from potential debtors has to be investigated, which contributes and maintains the segment's continuous spread. The analysis is divided into two main parts. In the first one the relationship between a wide range of economic indicators and P2P expansion is explored. Then the borrower characteristics are investigated, where the debtors are classified into different groups based on similar patterns.

The sample used for the analysis is a unique, manually collected database, including more than 135,000 loan applications from Prosper, which is one of the market leader platforms in the United States. The applications were published on the webpage of the platform in textual format between 2014 and 2020. After manual data collection, the information was transformed into table format using data manipulation techniques. Besides that, different state level national statistics were collected covering e.g., average credit profile, indebtedness, and financial and social features of the applicants' households. The data is coming from various sources, specifically: Economic Inclusion, Experian, Federal Reserve Bank of New York, Federal Reserve, United States Census Bureau, Kaiser Family Foundation, Bureau of Economic Analysis and Federal Deposit Insurance Corporation.

In the first part, LASSO regression analysis was applied to find relation between a wide range of macroeconomic indicators and the demand for peer-to-peer lending by state. LASSO is considered a useful technique when the number of observations is small and there are several potentially explanatory variables. It can improve the accuracy of the estimation, while producing easily interpretable results. The algorithm applies shrinkage, meaning that coefficients are shrunk towards zero and variables with zero coefficients are excluded from the regression. The mentioned six years are not split into further sub-samples as this time horizon

[1] Ölvedi, T. (2022). The Characteristics of Peer-To-Peer Applicants. The Journal of Alternative Investments, 25(2), 66-86.

is a prospering period for the emerge of marketplace lending, which could serve as a basis for robust outcome. The comprehensive microeconomic and socioeconomic database was produced and linked to the Prosper dataset aggregated by state and by year. The dependent variable in the analysis is the number of applications in each state and the potentially explanatory ones are 28 economic variables.

In the second part, cluster analysis was performed. The purpose of this investigation is to identify patterns in the population and form groups based on those patters. The point of the analysis is both to find similarities within the groups and differences between them. The K-means clustering method was chosen, which is one of the most commonly used approaches. K-means clustering aims to find the number of clusters, represented by K, based on the mean (or centroid) of the groups. The following variables were used for the analysis: revolving credit balance, current delinquencies and FICO average. Based on the Elbow method, the optimal number of clusters is four. Therefore, the value of K was set to four and k-means clustering iteration was performed.

2.2 The liquidity aspects of peer-to-peer lending[2]

The second paper examines the market from liquidity point of view. Most of the previous studies have focused on the credit risk aspect; however, we should be aware of the liquidity view of this alternative investment from the investors' perspective. In recent years, several platforms shut down their secondary markets due to a low number of transactions; however, after the COVID-19 outbreak, the demand for liquidity increased in the beginning of 2020.

The basis of the analysis is a large secondary market dataset, covering more than 5 million listings from a noted Estonian platform, Bondora. The marketplace provides a publicly available data set, which is updated daily. The data cover the actual portfolio table and the historical secondary market transactions in two separate tables. The portfolio table contains information regarding the loan characteristics issued on the primary market, the social features and the financial background of the borrower. The secondary market table covers the loan characteristics of the claim on the secondary market and its performance since listing. The sources can be merged together with a unique loan ID to include more variables in the analysis,

[2] Ölvedi, T. (2022). The liquidity aspects of peer-to-peer lending. Studies in Economics and Finance, 39(1), 45-62.

13 altogether. Besides that, four variables were created. The time interval of the sample comprises 18 months of historical data, from 01.02.2019 to 01.08.2020.

Three liquidity dimensions were defined, specifically the selling rate, average selling time and the level of discount. As a first step, these dimensions were examined with heatmap, meaning that each variable was analyzed in a matrix based on the days past due and rating. The rating is based on the platform's internal credit risk assessment process, using data provided by the applicant and also information about historical performance from the Credit Bureau system. As a next step, the determinants of a successful resale, selling time and discount rate were investigated. Different regressions were performed for the analysis, according to the nature of the data and the research problem. The question here is whether the variables significantly impact investor behavior during a successful transaction using the mentioned liquidity dimensions. Logit regression was applied for successful resale and linear regression for selling time and discount rate examination.

The previous years were characterized with economic prosperity and robust market expansion for the marketplaces; therefore, it is also relevant to investigate how the secondary market reacts in case of an external shock, caused by a pandemic situation. The second part of this study is also an introduction to the fourth paper, discussing the early analysis of the COVID-19 crisis. The data was split into two sub-samples based on the outbreak of the pandemic in March 2020 to examine the effect of these uncertain conditions on the secondary market. Regressions presented in the first part were performed again for the two separate periods (using the same variables which proved to be significant) to check how the relationship changed between the liquidity dimensions and the explanatory variables before and after the breakpoint.

2.3 Peer-to-peer lending: legal loan sharking or altruistic investment?[3]

The third study investigates the potential advantage of the marketplaces regarding information processing. The platforms assess applicants based on their own scoring methodology using standard variables and they also include alternative information which is not applied in case of traditional bank lending. Investors often rely on these internal ratings during their funding decision; therefore, it is expected that the ratings properly reflect the credit risk of the potential

[3] This paper is a joint work with Barbara Dömötör and Ferenc Illés.
Dömötör, B., Illés, F., & Ölvedi, T. (2023). Peer-to-peer lending: Legal loan sharking or altruistic investment? Analyzing platform investments from a credit risk perspective. Journal of International Financial Markets, Institutions and Money, 86, 101801.

borrower. To investigate the performance of the platform's model, a benchmark model was prepared using only standard variables which are frequently applied by banks. Besides that, the historical return of investors was also analyzed.

The modelling sample covers more than 107 000 observations of an Estonian platform, Bondora between the period of 2012 and 2019. At the time of our analysis, loans were available to borrowers in 4 countries: Estonia, Finland Slovakia and Spain. Bondora provides different datasets, which are updated daily. We used two types of datasets: first, the raw data of the loan book containing all loans with different applicant-related and other variables and, second, the historical payment table that includes all cash-flow series of each loan.

To investigate the performance of the platform's scoring model, we built a benchmark model using publicly available standard variables, usually included in the credit risk assessment process of a commercial bank. We created a default flag accordingly and considered a borrower to be in default if they were more than 90 days in arrears in the 12 months following the origination of the loan. We used this default definition for modeling and also when presenting ex-post default frequency. For our benchmark model, we selected 12 standard variables related to the financial position of the borrower, their previous loan history, and a few social features. The variables were selected taking into account the relevance of the data for scoring and their availability. We estimated the GINI coefficients that reflects the explanatory power of the variables and filtered out a few variables based on that. To build a scoring model, we ran different logistic regressions and selected the final model based on intuition and economic interpretation of the betas. Using the beta coefficients of the final model, the score for each observation was estimated. This was transformed into the probability of default. As a next step, we estimated the ROC curve to check the classification power of the model. Then, we compared our results with the platform's estimation to find evidence of the role of potential alternative data used by the platform. We also performed out-of-sample testing to check the default prediction performance on the independent data horizon.

Finally, the historical return of investors is also estimated to gain better view regarding the expected loss of these investments. We examined the dataset of historical payments, with the principal and the interest amount paid each month by loan ID. We calculated the IRR for each loan based on the cash-flow and the historical payment schedule.

2.4 The resilience of the peer-to-peer market: a global perspective[4]

The last research examines the segment in the period of economic downturn represented by the COVID-19 crisis. The pandemic outbreak had a significant impact on the economy and the financial sector, and the long-term consequences of the crisis are still unpredictable. The previous literature mostly focused on the time of economic prosperity, while there is limited research on the downturn period. The purpose of this paper is to contribute to the understanding of the segment in the case of economic distress.

The dataset covers 61 countries with diverse economic background. The data comes from two sources. First, the macroeconomic and financial indicators - reflecting the pre-COVID period of the economy and banking system - were downloaded from IMF and the GlobalEconomy.com. The time horizon of the data set covers the period of 2017-2019. The average of these three years was calculated in the analysis in order to properly capture the recent trends before the pandemic outbreak. The second source is the Cambridge Centre for Alternative Finance (CCAF), from which the lending volume of the peer-to-peer segment was obtained on the country level. The time horizon of the data includes the years of 2019 and 2020. The percentage change in the volume of marketplace lending was estimated for each county to reflect the behavior of the market during the shock.

In the first part of the analysis, different economic and financial indicators were selected before the time of the pandemic outbreak. All indicators were investigated in the previous P2P literature and were considered relevant from a platform perspective. Then k-means clustering is performed to identify similar patterns in the dataset and form groups based on that. K-means clustering is chosen which is one of the most commonly applied unsupervised machine learning algorithms. In order to define the optimal number of clusters, the elbow function is estimated.

In the second part of the analysis, two-sample t-test is performed in order to examine how the P2P market reacts during an external shock, in the case of each cluster. The reaction of the market is captured by the change in the lending volume from 2019 to 2020. The purpose of the test is to examine if there is a significant difference in the mean values across the clusters; therefore, pairwise combinations are analyzed. As a robustness check, the analysis is conducted from the other way around. Countries are grouped based on their reaction to the pandemic and the economic background of each group is compared.

[4] The paper is under consideration in Metroeconomica

3. Results of the dissertation

Based on the theoretical overview of the dissertation and the four papers presented above, it can be suggested that marketplace lending brings significantly higher risk, compared to conventional lending and investors are not necessarily compensated. The segment is still vulnerable in case of an external shock and the trust needs to be build towards this alternative funding model. From the other side, the platforms serve mostly underbanked customers. Therefore, there is a potential in them to have an important contribution from social perspective as they provide funding for less credible borrowers. However, in order to maintain long term successful operations, it is essential to introduce a comprehensive regulatory framework which enhances the credit risk management, investor and borrower protection and transparent operation of the platforms.

The detailed results of each study are presented below.

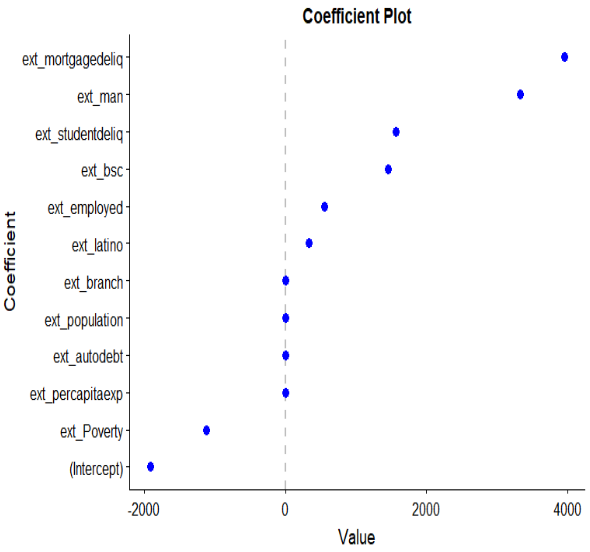
3.1 The characteristics of peer-to-peer applicants

According to the results of the LASSO regression (Table 1 and Figure 2), mortgage delinquency has the highest positive coefficient, which implies that the number of P2P applicants is higher in states where the mortgage delinquency rate is high. Therefore, it suggests that applicants probably utilize the P2P loan to refinance their overdue mortgage debts from a commercial bank. This assumption is supported by the previously presented fact that debt consolidation is the most frequent loan purpose. This result is in line with the research of Cornaggia et al. (2018) who found that loan delinquency and charge-off activity performed by small commercial banks is in line with peer-to-peer expansion. According to their explanation banks lowering credit requirements due to increased competition with the platforms and provide entry to less credible debtors. The finding is also supported by Maggio et al. (2017) who examined the relation between credit market and local economic factors related to mortgages and credit card balances. According to their conclusion, economic uncertainty due to high-risk borrowers is positively correlated with housing market illiquidity. Furthermore, the result is consistent with Buchak et al. (2018) who found that shadow banks, including fintech lenders gained a significant market share in refinancing in the residential lending market, mostly due to their lower regulatory burden.

1. Table: Result of LASSO regression

Variable	Coefficient
(Intercept)	-1 913.602
ext_autodebt	-0.003
ext_mortgagedeliq	3 950.343
ext_population	0.000
ext_bsc	1 458.809
ext_poverty	-1 118.645
ext_studentdeliq	1 560.321
ext_man	3 330.643
ext_latino	334.881
ext_employed	557.372
ext_percapitaexp	-0.015
ext_branch	0.106
R^2	77.21%
No. of observations	336

2 Figure: Coefficients of LASSO regression



Source: Author's estimation based on Prosper listing data 2014-2020
Note: The description of the above presented variables is the following:
ext_autodebt: auto debt, ext_mortgagedeliq: portion of mortgage delinquency, ext_population: population, ext_bsc: portion of bsc degree, ext_poverty: poverty rate, ext_studentdeliq: portion of student delinquency, ext_man: portion of man, ext_latino: portion of latino population, ext_employed: portion of employed residents, ext_percapitaexp: personal expenditures per capita, ext_branch: number of branches

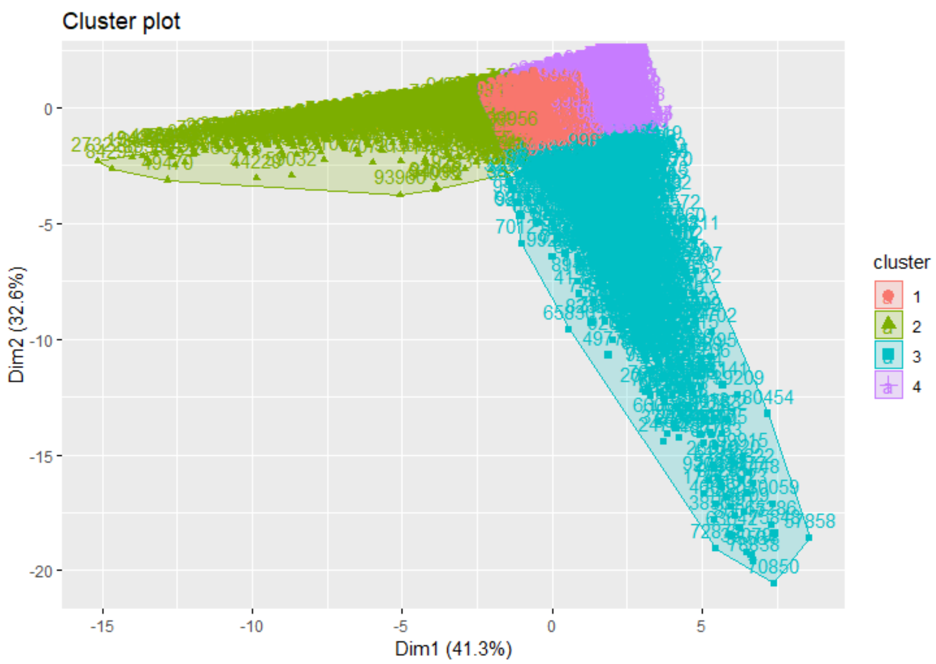
Based on the cluster analysis, four types of applicants can be differentiated (Figure 3), having the following characteristics:

- Group 1 applicants have with strong credit backgrounds and good credit history, with low levels of current claims. They are bank eligible; however, they might choose social funding due to more favorable conditions.
- Group 3 applicants seem to be bank eligible based on their FICO score; however, their revolving credit balances and bankcard utilization are quite high, and they request the highest loan amounts. The DTI ratio is also the highest, although their income covers the revolving debt. It can be suggested that they have immediate liquidity needs which might be funded faster by the platform compared to a bank process.
- Group 2 applicants probably face constraints upon bank funding, as their average FICO is relatively lower and they have delinquencies in their previous loan history; thus, obtaining a social loan could be easier than conventional funding.

- Group 4 applicants are likely not bank eligible as their average FICO is the lowest, and they have significant delinquencies in their loan history; therefore, they must necessarily explore alternative forms of finance.

Overall, the results suggest that P2P lending has dual function on the credit market: it supplements bank lending for a small segment of customers and for most of the cases it substitutes bank funding. The mixed role of the platforms on the consumer credit market is further supported by Tang (2019) who identified the importance of the loan size in this matter. According to his study, platforms are complements for banks in case of small loans and substitutes contrarily. This is in line with the results of the cluster analysis, as Group 2 and 4 have the lowest FICO score, coupled with smaller requested loan amount. The complementary approach is supported by Cole et al. (2019) who concluded that bank failures are associated with decrease in the volume of crowdfunding. However, their study focused on project finance instead of retail lending, where the complementary function of alternative finance is probably more dominant.

3. Figure: The distribution of Prosper applicants based on k-means clustering



Source: Author's estimation based on Prosper listing data 2014-2020.
Note: The clustering is based on the following variables: revolving credit balance, current delinquencies, and FICO average.

3.2 The liquidity aspects of peer-to-peer lending

The heatmaps show that the market is relatively liquid, with the average selling time being around 1.5 days (Table 2). A relatively short resale period is further supported by the platform's practice. Investors have the opportunity to use the service of a portfolio manager, who buys and sells loans automatically on the secondary market, based on previously set parameters for speeding up the process (Bondora, 2020).

2. Table: Average selling time split by rating and days past due (DPD), which means the number of days in payment delay from the time when the loan was listed on the secondary market

DPD	AA	A	B	C	D	E	F	HR	Standard deviation
0	0.83	1.65	1.13	1.45	1.52	1.50	2.06	1.94	6.49
1-30	5.05	6.87	4.36	4.54	4.35	3.67	3.90	3.63	11.08
31-60	4.77	5.51	3.35	3.55	3.61	3.15	3.22	2.51	10.25
61-90	2.03	3.07	2.63	2.09	1.90	2.10	2.08	1.84	7.99
91-120	0.72	0.87	2.05	1.79	1.34	1.67	1.23	0.86	7.11
120+	1.12	0.91	0.84	0.75	0.94	0.86	0.70	0.67	5.72

Source: Author's estimation based on the Bondora secondary market database as of August 2020

The highest demand is for performing loans with 0 days past due (DPD), and the proportion of selling decreases in line with worsening performance (Table 3). The selling rate does not depend on the rating; instead, investors use the information regarding days past due. Rating has significant role on the primary market, and it mainly serves as a basis for investor funding decisions (Herzenstein et al. 2008; Gavurova et al. 2018). However, the rating methodology is a "blackbox", its accuracy was examined in several studies (Jagtiani and Lemieux 2019; Bhuvaneswari and Segalini, 2020; Byanjankar et al. 2015). The role of days past due on the secondary market is reasonable as it can be considered as the most up to date information, reflecting the actual performance, while rating is related to historical experience.

3. Table: Portion of successfully sold loans split by rating and days past due (DPD), which means the number of days in payment delay from the time when the loan was listed on the secondary market

DPD	AA	A	B	C	D	E	F	HR
0	67%	58%	67%	72%	75%	75%	77%	75%
1-30	41%	41%	50%	51%	52%	48%	44%	49%
31-60	43%	40%	50%	49%	46%	41%	48%	48%
61-90	38%	35%	43%	46%	46%	42%	40%	40%
91-120	38%	31%	43%	40%	35%	39%	32%	33%
120+	33%	27%	35%	34%	32%	35%	39%	34%

Source: Author's estimation based on the Bondora secondary market database as of 2020 August

Finally, discount rates are relatively high and performing loans are sold with a discount, which suggests that the price of liquidity has to be paid by the seller (Table 4). As a comparison, bank sale discounts reached ~28% in Europe for NPL portfolios. It has to be emphasized that is hard to compare the P2P discount rates with bank sale discounts, as numbers vary based on the selected time period and portfolio.

4. Table: Average discount rate split by rating and days past due (DPD), which means the number of days in payment delay from the time when the loan was listed on the secondary market

DPD	AA	A	B	C	D	E	F	HR
0	-5.78%	-6.13%	-6.77%	-4.96%	-3.45%	-3.17%	-2.94%	-4.17%
1-30	-9.15%	-7.75%	-12.00%	-12.03%	-13.09%	-14.03%	-9.90%	-12.54%
31-60	-12.99%	-12.99%	-20.31%	-20.71%	-21.14%	-20.17%	-14.08%	-21.23%
61-90	-16.53%	-19.24%	-22.77%	-23.52%	-26.74%	-26.20%	-17.70%	-21.76%
91-120	-19.97%	-21.08%	-24.28%	-21.57%	-24.59%	-28.71%	-17.55%	-22.40%
120+	-23.50%	-24.46%	-25.92%	-26.48%	-27.44%	-26.61%	-22.46%	-27.65%

Source: Author's estimation based on the Bondora secondary market database as of August 2020

According to the regressions, in terms of successful resale, the discount rate, the amount of principal at start, the country of the borrower and the time passed from loan origination proved to be significant. For selling time and discount rate the model fit was low.

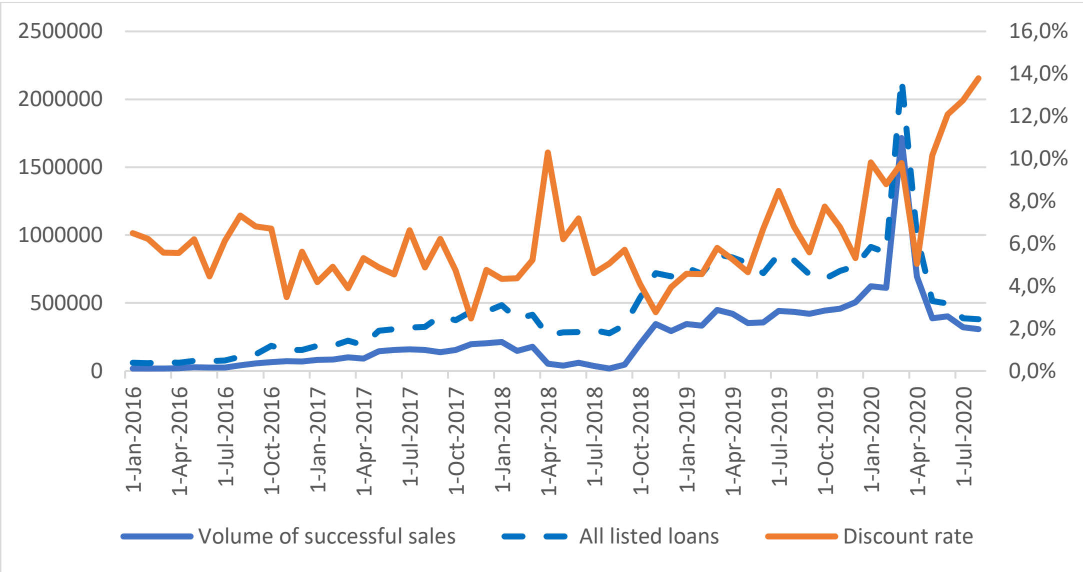
5. Table: The results of logistic regression for the probability of successful resale as a dependent variable

Variable	Coefficient	Marginal Effects	Std. Error	z-value	Pr(>|z|)
(Intercept)	3.2140		0.0045	705.17	0.0000 ***
DiscountRate	-0.0413	-0.0098	0.0000	-611.81	0.0000 ***
log_PrincipalAtStart_2	-0.0104	-0.0024	0.0004	-25.61	0.0000 ***
CountryES	-0.3305	-0.0808	0.0038	-86.35	0.0000 ***
CountryFI	-0.2284	-0.0552	0.0023	-98.33	0.0000 ***
log_from_origination	-0.5567	-0.1331	0.0007	-747.36	0.0000 ***
No. of observations	5 112 566				
AUC	0.75				

Source: Author's estimation based on the Bondora secondary market database as of August 2020
Note1: In case of Country, which is a categorical variable, class "EE" was taken as the reference, which means Estonia
Note2: Discount rate is in percentage (%) format.
*Note3: *** indicates the significance at the 99% level, respectively*

In terms of COVID impact, Figure 4 presents the aggregated volume of all listings, aggregated successful resales and monthly average discount rate, from January 2016. In terms of resale volume, there was a significant increase in March 2020 when the pandemic started to grow rapidly across Europe, and the volume dropped in the next period. A strong co-movement can be observed between the volume of successful sales and all listings. Discount rate has a volatile trend; however, from April 2020, the level of fare reduction started to increase. This indicates that investors started to liquidate their money and were willing to provide higher discounts in the dropped demand environment.

4. Figure: The volume of all listings, successful resales, and the level of discount rate between 01.01.2016 and 01.08.2020



Source: Author's estimation based on the Bondora secondary market database as of August 2020
Note: the right axis belongs to the discount rate and the left to the volumes

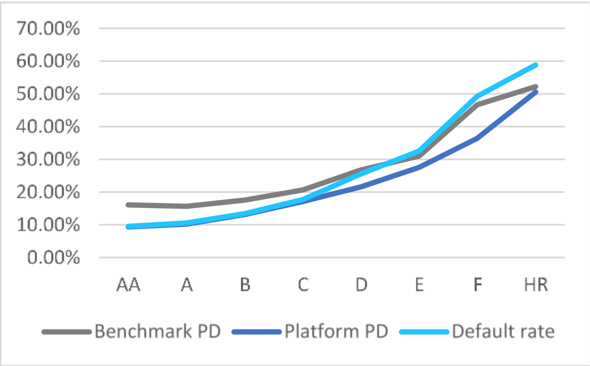
To examine whether an external shock causes any significant change in the secondary market, the data was split into two subsamples and regressions were performed to check how the relationship changed between the liquidity dimensions and the explanatory variables before and after the breakpoint. The results show that the slope and the betas differ in the sub-samples for the three liquidity dimensions. However, all the independent variables remained significant at the 1% significance level for all the regressions. The difference suggests that there is a structural break in the data series in relation to the growth in pandemic, which is in line with the trend presented in Figure 4.

3.3 Peer-to-peer lending: legal loan sharking or altruistic investment?

When comparing our benchmark model to the results of the platform, the figures show that the platform underestimates the probability of default for all rating grades. Our model's in-sample estimation is a little closer to the observed default rates for the worse rating categories than the platform's results, however, we overestimated the probability of default for the best rating category. The average probability of default for each rating category based on our model (Benchmark PD), the PDs estimated by the platform at origination (ex-ante), and the real default rates using our default definition are presented in Figure 5.

5. Figure: Comparison of the ex-ante Model PDs and the Observed Default Rate

Rating	Benchmark PD (ex-ante)	Platform PD (ex-ante)	Default rate (ex-post)
AA	16.02%	9.32%	9.49%
A	15.66%	10.22%	10.52%
B	17.54%	13.15%	13.40%
C	20.58%	17.10%	17.73%
D	26.75%	21.56%	25.57%
E	30.97%	27.52%	32.49%
F	46.69%	36.37%	49.29%
HR	52.16%	50.51%	58.80%

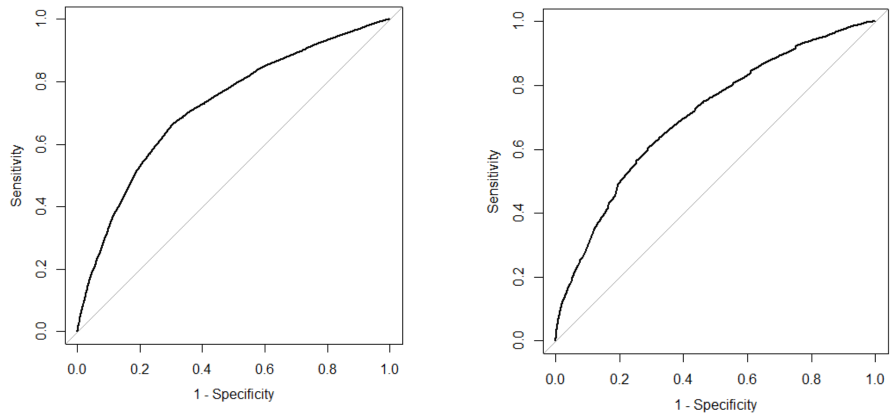


Source: Bondora webpage as of 2020 October

We estimated the ROC curve to check the classification power of the models (presented in Figure 6). Our benchmark model's in-sample performance resulted in a GINI of 44.10%, while the platform's classification achieved a GINI of 41.08%. The goodness of these GINI values is hard to judge. In the case of a commercial bank, a retail scoring model is expected to achieve a GINI higher than 80%, but for special, high-risk portfolios, significantly lower GINIs may also be acceptable. On the other hand, Jagtiani and Lemieux's (2018) model obtained a GINI of 38% (Area under the ROC curve 69%), even for the best-performing variable set. The in-sample GINI we could achieve was only slightly higher than the GINI of the platform's model for the same period. Therefore, we can confirm that the platform's model performs appropriately. However, the performance of our benchmark model suggests that a similar result can be achieved based on a classic "banking-like" information dataset. Hence, in our investigation, we could not detect any sign of the benefits of using alternative data sources or information processing of fintech lenders. The out-of-sample results are in line with the in-sample outcomes.

The GINI of our model is 43.28%, only slightly below the in-sample value. The analysis of the platform's PD resulted in a GINI of 37.92%.

6. Figure: Comparison of the ROC (Receiver operating characteristic) curves in-Sample



Source: Bondora webpage as of 2020 October

Note: The figure on the left shows our model's curve, and the one on the right is the curve of the platform's model.

In terms of investor returns the results are presented in Table 6. We included in the analysis transactions with closed status and also loans where the original maturity (calculated from the date of issuance and the original loan duration) is exceeded at the time of data collection or where no payment was made in the last one-year period. We assume here that these transactions can also be considered closed as there will be no further related payments. The average IRR of the portfolio is negative, which means that investors on average not only do not receive compensation for the risk, but also make a loss on their original investment. The average IRR is negative even in the best rating categories, with only rating C, HR, and the unrated transactions resulting in a positive IRR. The IRR dispersion is high, but overall 41.63% of all transactions have a negative IRR and the realised loss is 55% of the amount invested (for transactions with a negative IRR, the nominal amount of payments received is on average 55% less than the initial investment). So, despite an average initial expected return of 9.58% - 15.52%, the average realised return is negative in most rating categories.

6. Table: Main Characteristics and Ex-Post Performance of the Closed Dataset

Rating	Number of loans	Default rate	Average loan amount	Average loan term (in days)	Average Sum CF	IRR mean	IRR st. Dev.	P(IRR < 0)
AA	3,701	9.92%	1,843.50	764.40	-96.31	-4.00%	29.42%	30.96%

A	4,867	11.42%	1,693.45	900.82	18.30	-3.49%	31.14%	36.47%
B	12,292	12.41%	2,042.84	864.78	25.13	-1.15%	32.08%	33.25%
C	17,116	16.68%	2,349.80	834.13	9.38	0.29%	37.58%	33.46%
D	18,544	25.04%	2,574.12	783.91	-185.74	-3.86%	46.59%	39.70%
E	17,660	29.85%	2,753.38	644.83	-340.97	-9.12%	53.03%	44.51%
F	16,374	44.99%	2,943.98	529.52	-584.43	-17.29%	68.88%	56.99%
HR	11,880	53.10%	1,760.87	726.39	-228.66	4.29%	116.83%	53.21%
NA	2,701	19.29%	643.52	767.04	148.63	24.93%	25.64%	5.96%
ALL	**105,135**	**27.98%**	**2,355.22**	**736.35**	**-201.15**	**-4.17%**	**60.36%**	**41.63%**

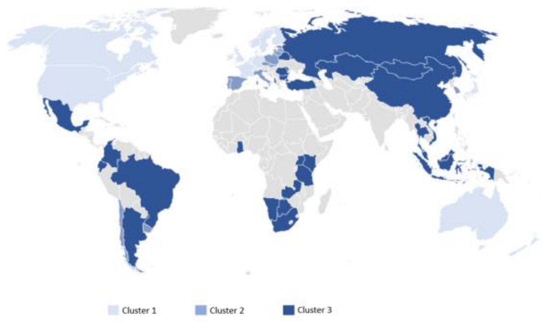
Source: Bondora, as of May 2022

3.4 The resilience of the peer-to-peer market: a global perspective

According to the cluster analysis based on pre-COVID economic and financial variables, three groups can be differentiated (Figure 7):

- Cluster 1 represents the most developed countries, having a strong economic background with robust per capita GDP, high living cost and low inflation. The financial institutions are accessible, reflecting extended branch and ATM network. The level of bank credit to the private sector is robust and the efficiency of the banking system is high. Furthermore, the banking portfolio has low NPL level.
- Cluster 2 presents moderately developed countries with restrained per capita GDP and significant unemployment rate. The banking portfolio has a good performance with an extended branch network; however, the depth of the financial institutions is low, leaving space for alternative financing opportunities on the market.
- Cluster 3 groups developing countries, having modest economic performance, evidenced by the relatively low GDP and high inflation rate. The lending activity of the banking sector is low, and the branch network is not extensive, coupled with moderate portfolio performance. The financial indexes imply that the access to credit is limited.

7 Figure: The final groups based on the clustering algorithm



Source: Author's estimation based on theGlobalEconomy.com 2017-2019

The t-tests imply that there is a significant difference in P2P volumes after the COVID, between groups in case of clusters 1-3 and 2-3, as the p-value is below 0.1. It suggests that the three clusters based on pre-COVID variables have a good classification performance in terms of P2P market reaction. Table 7 summarizes the change in mean value of the P2P volume in the three clusters.

7. Table: The P2P volume change in each cluster

Cluster	Mean of P2P volume change
1	-9 %
2	20 %
3	865 %

Source: Author's estimation based on CCAF 2020

The trend of marketplace lending clearly differs in the three types of economies. Cluster 1, which represents the most developed countries, showed a moderate decline of -9% in its lending volume. It might be explained with the high living standard and their stable and extended banking system which has the ability to manage those who are facing financial difficulties. In addition to that, countries belonging to this cluster have quite developed P2P market in general, where the regulatory framework is constantly expanding, especially in the United Kingdom, Australia and the United States (Davis, 2016; Magee, 2011; FCA, 2019), providing a burden to finance clients with poor credit background. In contrast, cluster 3 which covers developing countries showed an excessively strong growth rate of 865%. The remarkable demand might be implied by the modest economic conditions and the weak banking system. The access to funding and the efficiency of the banking system is underdeveloped, making platform lending more beneficial anyway. Besides that, the high level of non-performing loans suggest that significant portion of borrowers are not bank eligible even during the times of economic prosperity.

Overall, the results suggest that during economic distress, the growth rate of P2P lending is in line with the economic and financial instability of the country. This finding is supported by previous literature from the time of economic prosperity, which highlights that the extension of marketplace lending is stronger in underdeveloped regions. Jagtiani and Lemieux (2018) found that in the US market, the lending volume increases in areas where the local economy has weaker performance. Polyzos et al. (2021) emphasizes that P2P expansion is in line with higher financial instability, unemployment, and lower GDP. Furthermore, Havrylchyk et al. (2017) explored that the lower level of bank network in the US supports the spread of platform lending.

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5. Relevant publications of the Author

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